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Research Article

Impact of Market Learning on Management Innovation: Mediating role of Knowledge Integration

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Abstract

Purpose- The article aims to study and explore the effect of market learning on management innovation along with exploring the role of knowledge integration as a mediator in the hospitality industry of Pakistan.

Design/Methodology- The data comprised 215 respondents from the hospitality industry, and it was gathered through a questionnaire containing 22 items, including four demographical items. The gathered data was utilized to validate our model empirically through statistical tests.

Findings- Research findings reveal that management innovation is driven by market learning, and significant relationships exist between market learning, knowledge integration, and management innovation. The mediating role of knowledge integration also exists significantly between management innovation and market learning.

Novelty – Knowledge integration about management innovation and market learning is a novel contribution, and findings suggest that its effect on this model is significant.

Practical Implications- Successful organizations include knowledge integration and management innovation as a critical part of their culture as these variables boost the firm's productivity and employee participation, and both are found to be driven by market learning. The managers can make an effort to enhance market learning and improve the firm's overall performance.

Introduction

Literature that follows market-driven organizational patterns has specifically introduced market learning as a significant provenance of innovation and solid execution (Day, 1994). According to the 1960s market pull approach to innovation, firms should examine the scope of new opportunities that are supposed to satisfy their customer base to be active innovators (Levitt, 2004). Arguments claim that Initiating point for innovation is through assembling and circulation of marketplace knowledge to form an innovative idea (Foxall & Fawn, 1992). To enhance the affectation and success of innovation, it is likely that the apprehension of market choices lessens the level of the discrepancy of the latest products with the requirements of the customer (Cooper & Kleinschmidt, 1987).

Using formal procedures and structures that allow capturing the market and other knowledge while integrating it in different functional units of an organization is defined as knowledge integration (Olson, Walker Jr, & Ruekert, 1995). The literature has identified different roots of knowledge integration. Out of these, teamwork is of the utmost gravity. Knowledge exchange between specialists resulting in improved solutions and new idea development is facilitated by teamwork (Becker & Zirpoli, 2003). Sharing of knowledge is not the only aspect of knowledge integration; instead of generating new knowledge is significant as people conjoin information they hold (Okhuysen & Eisenhardt, 2002). In light of dynamic capabilities view (Eisenhardt & Martin, 2000), we can conceptualize that attaining new knowledge through internal or external means leads to innovative service firms where this knowledge adds up to the existing one. In this intensifying competitive business environment, firms are required to focus on their management model innovation to sustain competitive advantage. Birkinshaw, Hamel, and Mol (2008) indicate that the primary reason for the success of P&G, DuPont, and GE is their innovation in their management models. Management Innovation is defined as the development and implementation of a management practice, structure, technique or process (Birkinshaw et al., 2008). Management Innovation helps to maintain a long-lasting competitive edge that becomes difficult to copy (Pisano & Teece, 2007). Management innovation significantly affects the organization's performance by gaining a competitive advantage. Emotional exhaustion of employees is caused by doing the same job task in the same manner, and emotional exhaustion has a direct and positive relationship with counterproductive work behavior (Luqman, Fatima, Ahmed, Khalid, & Bhatti, 2020). Therefore, management innovation is vital to boost employee performance in the organizations. Management practices and structures have economical as well as social influence on the firm. For firms to attain a competitive edge, management innovation has been argued to be the dominant and feasible origin (Hamel, 2006). It is becoming a problem of value as firms search for ways and means to enhance their productivity and competitiveness in the global market.

Previous studies mostly focused on the adoption of this process and a successful transition after the adoption. However, new technologies are often not adopted in their current form but adapted by the firms while in the process (Rogers, 2003). Literature has focused chiefly on technological innovation; however, the horizon of management innovation remains unexplored. Despite this, with the availability of resources, firms are investing more towards management practices to gain a competitive edge (Bromiley & Rau, 2014). Prevailing management practices, processes, and diaphragms are being revised by firms to encourage firm performance. The relationship between management innovation and market learning has been part of literature in the past. Still, the incorporation of knowledge integration as a mediator is a new contribution to literature. This research aims to fill the gap of knowledge integration as a mediator between management innovation and market learning.

The significance of this study is that it can help many firms to reinvent their management models to be successful in today's competitive world. Large scale organizations have specific formal procedures to implement new ways of management, while small scale firms can quickly implement new management ways, which are

crucial for their success. Google has an entirely different model of management in which employees have freedom in their work, and they focus on innovation. Mol and Birkinshaw (2009) described that management knowledge could be acquired through productive market learning, and it will help to break the inertia in the management innovation process. Hence, the companies that focus on market learning are more likely able to reinvent their management models. Previous studies show that the innovation potential of a firm can be increased by collecting knowledge from different stakeholders (Slotegraaf, 2012), by spreading a market/learning-oriented environment (Marinova, 2004), and promoting knowledge sharing behavior within the firm (Arnett & Wittmann, 2014). Therefore, market learning and knowledge integration are crucial in the management innovation process of a firm.

This study aims to explore the relationship between Market Learning, Management Innovation, and Knowledge Integration. The first objective of this paper is to study the relationship between Market Learning and Management Innovation. The second objective of this paper is to study the relationship between Market Learning and Knowledge Integration. The third objective includes the study of the relationship between Knowledge Integration and Management Innovation. The fourth objective is to explore the mediating effect of Knowledge Integration between Market Learning and Management Innovation. This research paper contains distinct objectives as we have Management Innovation as a dependent variable; we are focusing on addressing innovation in the field of management. Management Innovation is essential because the companies which have innovated their management models like HCL Technologies and W. L. Gore have experienced so much success. HCL Technologies is a company that follows a 360-feedback management practice in which the subordinates are required to give feedback about their leaders. W. L. Gore is a company, and they have management in which job titles are not given to the employees of the organization.

In contrast, employees have a set of responsibilities. These disruptive management models are the key features behind the success of these organizations. In this way, innovation in management practices enhances employee participation and productivity, and it leads to the success of the organization.

The rest of this research paper is organized in the following manner. The Literature review section contains the relevant arguments on Management Innovation, Market Learning and Knowledge Integration, and all four-hypothesis defining the relationship between these variables. The methodology section entails the details of the research method and the demographical details of the respondents in this paper. Next, the analysis section conceptualizes the responses of this study and relationships among variables. The findings section represents the study findings and the significance of these variables. Lastly, the paper contains the limitations of this study with directions for future research.

Literature Review

Market Learning and Management Innovation

Market learning refers to the new ideas and knowledge acquired from outside the boundaries of the company (Wang & Yang, 2018). Weerawardena (2003) defines market learning as it includes the knowledge about customers' needs and strategies of competitors. The literature of management innovation requires equal attention from the researchers concerning technological innovation. Bromiley and Rau (2014) state that management practices in firms have a high level of investment to achieve and maintain competitive advantage as the resources are easily accessible. In other words, Management innovation is defined as using new management practices or ideas in an organization (Wei, Song, & Xie, 2019). Therefore, the concept of MI has high significance in order to outperform the competitors and develop good reputation.

Management innovation aims to achieve a better managerial system in the organization by considering the external sources of knowledge. Managerial systems that are not fit for the organization must be addressed, and

new practices should be implemented for a better routine system (Lin, Murphree, & Li, 2017; Volberda, Van Den Bosch, & Mihalache, 2014). The management capability of a company can be judged by external stakeholders based on management innovation (Wei et al., 2019). Therefore, management innovation helps build a sharp firm image for the external stakeholders, which exhibits excellent management capability of the firm. The organization which focuses on innovation, develop and polish market learning capabilities can gain and sustain competitive advantage and are more valuable for its customers (Weerawardena, 2003). This argument gives us insight that market learning is crucial for the process of MI. Khosravi, Newton, and Rezvani (2019) states that MI has a definite relation to organizational learning. Carboni and Russu (2018) define that market knowledge is crucial to break the inertia and innovate the management of the organization. Hence, market learning has a positive impact on management innovation, and it creates opportunities to identify and implement the right management practices in the organization.

Hypothesis 1: Market learning has a positive relationship with management innovation.

Market Learning and Knowledge Integration

The knowledge and information gathered by the company from the outside of its boundaries are defined as market learning (Kim & Atuahene-Gima, 2010). Market knowledge is crucial in creating opportunities for management innovation, and it enables firms to pursue new management practices and approaches. Market learning is highly significant for any organization that is trying to gain a competitive advantage. Wilden and Gudergan (2015) provide evidence that to develop the firm's capabilities, including technological and non-technological, the firm must have to gather market information effectively and integrate the knowledge that is valuable for the firm. Hence, learning from the market and integration of that knowledge is significantly co-related and gives a clear insight into the development of the organizational capabilities.

The innovation process of a firm can be improved by combining the existing and newly acquired market knowledge, and knowledge integration can be done effectively when there are proper integration and operational mechanisms (Azadegan, Dooley, Carter, & Carter, 2008; Berggren, Bergek, Bengtsson, Söderlund, & Hobday, 2011; Lane, Koka, & Pathak, 2006; Martín-de Castro, López-Sáez, Delgado-Verde, & Koch, 2011). Existing knowledge and new market knowledge is equally essential to develop the best management practices in the organization that are beneficial for the organization and attractive for the external stakeholders. Knowledge integration enables the firm to share valuable information and make it widely available within the organization. It is evident that entrepreneurial organizations focus on market learning and actively implement knowledge integration in the technological and managerial practices that create value for the organization (Weerawardena, 2003). Therefore, market learning is significant to obtain a competitive advantage by integrating the acquired knowledge within an organization for better decision making about different areas of management systems.

Hypothesis 2: Market learning has a positive relation to knowledge integration.

Knowledge Integration and Management Innovation

The propensity to fuse knowledge inside and outside the organizational parameters is known as knowledge integration. Companies use knowledge as a central resource to preserve an enduring competitive edge (Maravilhas & Martins, 2019). Effectiveness of knowledge integration is influenced by the quality of knowledge gained. To integrate knowledge is a procedure to store and evolve knowledge (Ahmad, Bosua, & Scheepers, 2014). Knowledge integration may help to steer a company's production procedures (Furlan, Vinelli, & Dal Pont, 2011). The project performance levels of different companies can be justified through integration ability. Internally accessible knowledge demands a shared viewpoint about future challenges or hurdles to allow the formulation of a new remedy by combining existing knowledge, according to Okhuysen and Eisenhardt (2002).

Social Interactions among individuals using internally available communication medium allows a shared perspective formulation. To pass on specific inside information, these inter-unit connections are fundamental (Tsai, 2001). Transmission of knowledge permits its reuse and its reconciliation, which is a major aspect of management innovation (Majchrzak, Cooper, & Neece, 2004).

The company's integration ability proves to be a priceless resource for employees with diverse kinds of knowledge. Internal communication is the central part of knowledge integration, as it can become multiplex in more prominent firms, hampering knowledge integration and its impact that correlates, in this scenario, management innovation (Mol & Birkinshaw, 2009; Walker, Damanpour, & Devece, 2011). Elevated levels of trust and collaboration are induced by higher networking in employees. Managers would use these results to incorporate managerial innovations at a higher level, improved understanding of business, and gain more knowledge to nurture new concepts (Jansen, Van Den Bosch, & Volberda, 2006). The extent of integration is mainly recognized by the motivation and skillset of employees (Collins & Smith, 2006). In knowledge integration, a shared vision of the firm is created in the organizational context, which allows the transfer and processing of inside and outside knowledge (Cummings, 2004). Thus, integration promotes the transmission of versatile data into a new format of integrated and original knowledge, supporting the innovation process (Salazar, Lant, Fiore, & Salas, 2012). The essence of this discussion helps us to formulate the hypothesis:

Hypothesis 3: Knowledge Integration is directly related to Management Innovation.

Market Learning, Knowledge Integration and Management Innovation

Firms must know the pre-requisites before entering a new market, handling cross-cultural scenarios, and setting a fresh mindset inside the organization (Anderson, Boocock, & Graham, 2001). Inadequate knowledge of the market's businesses and institutes could result in mounting unrecognized costs and risks, which hinders the firm's expansion (Eriksson, Johanson, Majkgård, & Sharma, 2000). Market learning focuses on the intuition and mental patterns of market behaviors, expectations related to firms' market, customer needs, competitor proficiency, market reactions to firm operations, and trends of existing market opportunities. The ability to adapt according to market type is necessary alongside precise market knowledge, according to Eriksson et al. (2000). Thus, market learning is the desired phenomenon at the firm level to enable promotion in multiple business conditions. Advancement of this process is suggested through the use of knowledge management systems, particularly knowledge integration. It allows proper positioning and acculturation of present knowledge for the formation of up-to-date knowledge. Members become more able to understand the consequences lead by their actions as part of the cause and effect process (Zollo & Winter, 2002). Having this system makes it easier to recognize customer needs and pinpoint market opportunities (Lu, Zhou, Bruton, & Li, 2010). At this point, assimilated procedures are interpreted into managerial expertise to cater to the needs of the firm's customer (Hamel & Prahalad, 1996). This knowledge integration process comprises three steps mainly to capture, interpret, and use the acquired knowledge inside the organization (Zahra, Ireland, & Hitt, 2000). We capture to allow better availability of information to firm members through documentation and trade-off. Interpretation plays its role to review and assess new information (Von Hippel & Tyre, 1995). In knowledge, an integration firm creates a standard in terms of the organization promoting external and internal knowledge transfer and processing (Cummings, 2004). Thus, integration promotes the transmission of versatile data into a new format of integrated and original knowledge, supporting the innovation process (Salazar et al., 2012). So, knowledge integration allows the flow of diversified information into the current format of integrated and authentic knowledge, assisting the innovation process. This argument leads us to the hypothesis:

Hypothesis 4: Knowledge Integration is mediating the positive relation between Market Learning and Management Innovation.

Theoretical Framework

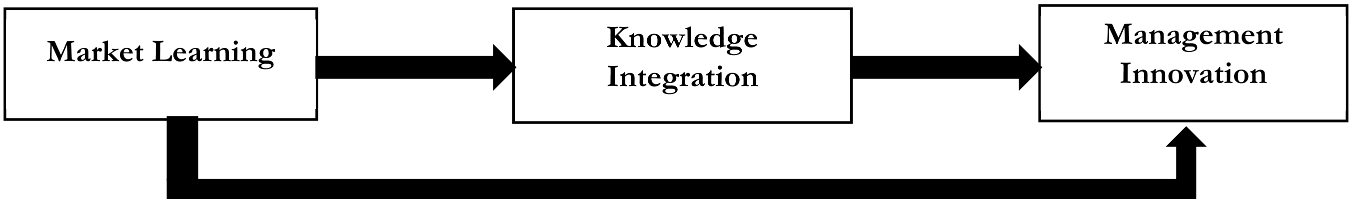

Figure 1 - Conceptual Framework

The model displayed in figure 1 is the theoretical framework of this study. The relationship between management innovation and market learning is positive because the market knowledge enhances the capability of a firm to induce innovation in its management practices. Market learning is related to knowledge integration as the market knowledge must be shared within the organization to keep everyone aware of the necessary information about the market conditions. The extent to which the knowledge is integrated within a firm determines the ability to innovate its management practices. In this way, knowledge integration takes forward the indirect effect, and it mediates the relationship between market learning and management innovation.

Methodology

This study uses the quantitative research method to explore the outcomes. Our survey helped us develop the findings in a specific time constraint as a result of the cross-sectional method being adopted. The hospitality sector of Pakistan was selected to be studied, giving us 215 responses through specified criteria. The Snowball sampling technique is used to gather data through a survey questionnaire as this research has been conducted during the COVID-19 pandemic. This research solely focused on the hospitality sector because of its growing scope in Pakistan. Investigation, purpose, and moral affairs were made clear from the start. The mechanism holds two sections. Firstly, the demographics of the respondent. Secondly, a complete study of variables. Our sample withholds a male percentage of 73.5 percent and 26.5 percent of females.

The prominent age groups in our responses were from 18-35 years. Five items Likert scale was used where 1 represents SD strongly disagree while five is for strongly agree. All the variables had a varied number of items in the questionnaire. Market Learning comprises nine items adaptation from Kim and Atuahene-Gima (2010), whereas Management Innovation holds four items adapted from Yang, Li, Jiang, and Zhao (2020). Similarly, Knowledge Integration resides with five items adjusted from Grant (1996) in the survey. Primary sources were inherited to collect data where employees of hotels and restaurants filled the surveys. Many statistical tests, such as KMO Measure of Sampling Adequacy, Reliability Analysis, and Regression, were applied to examine the gathered data.

Analysis and Results

The number of respondents in our data is 215, and data is gathered from the employees of the hospitality industry. In our data, 73.5 percent was the proportion of males, and 26.5 percent was the proportion of females. The data constituted of 66.5 percent of 21 to 30 years, 27 percent of 31 to 40 years, 5.6 percent of 41 to 50 years and 0.9 percent of 51 or above years of age. 2.8 percent of respondents have Intermediate degrees, 28.8 percent of respondents have a graduation degree, 66 percent of respondents have a Masters MS/M Phil degree, and 1.4 percent of respondents have other degrees. The income group of 20,000 to 34,999 PKR is 32.6 percent, 35,000 to 49,999 PKR is 25.1 percent, 50,000 to 64,999 PKR is 26 percent and 65,000 PKR or above is 16.3 percent.

Factor analysis has given the KMO value of 0.951, which manifests that our sample size is highly adequate, and the p-value is less than 0.001, as shown in table 1. The items loaded of each variable in the pattern matrix is

represented in table 2. The reliability analysis manifests the value of Cronbach's Alpha is 0.962, which higher than the degree of 0.65, and it shows that the items in our research are internally consistent, as represented in table 3. Correlation analysis shows that the correlation of the variables is significant at the level of 0.01, as manifested in table 4.

Table 1 - KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.951**
Bartlett's Test of Sphericity	Approx. Chi-Square	3549.409
	df	153
	Sig.	.000

Table 2 - Factor Loadings

Codes	Statements	Loadings
1. **Management Innovation**		
MI1	We regularly implement a new routine for finishing the task.	.866
MI2	We regularly implement new ways to enhance the degree of employee satisfying and efficiency of work procedures.	.865
MI3	We regularly implement new processes and systems.	.852
MI4	We regularly implement a new way to achieve the target.	.811
2. **Market Learning**		
ML5	Used market information and ideas involving experimentation and high risk.	.895
ML4	Used market information and ideas with no identifiable market needs	.876
ML8	Used market information and ideas that may contribute to the firm's existing product markets.	.872
ML3	Used novel product/market ideas that may not necessarily be successful in the current markets.	.859
ML2	Used market information from lead users that forces project team members to learn about new things in our markets.	.831
ML7	Emphasized using proven ideas for solutions to marketing problems.	.826
ML9	Undertook activities that help to utilize or integrate the firm's current market experiences	.817
ML6	Used new ideas that are consistent with our current product- market experiences.	.791
ML1	Used market information that takes the firm beyond its current product market experiences.	.783
3. **Knowledge Integration**		
KI3	There were generally accepted behavior patterns that governed actions when rules and procedures did not.	.861
KI2	The firm had production activities divided into independent phases and organized sequentially.	.855
KI1	The rules/policies of the firm enabled the coordination of activities and information flows.	.851
KI4	The organization resolved uncertainty through conflict resolution and decision-making groups.	.833
KI5	The rules, sequences, behaviors patterns, and groups enabled useful sharing knowledge among members of the firm, avoiding unnecessary transfers.	.792

Table 3 - Reliability Analysis

Variables	Number of items	Reliability (α)
MI, ML, and KI	Total = 18	.962
Management Innovation	4	.909
Market Learning	9	.958
Knowledge Integration	5	.917

Table 4 - Correlation Analysis

Correlation	ML	KI	MI
ML	1	.695**	.674**
KI	.695**	1	.653**
MI	.674**	.653**	1

Note: **Correlation significant at 0.01 level.

Hypothesis Testing

Hypothesis 1: Market Learning has a positive relation with Management Innovation.

The assumed hypothesis is supported as the p-value is 0.000, which is significantly smaller than 0.05 degree, as displayed in table 5. The Standardized Coefficients β is 0.674, which exhibits that increase in 1 unit of Market Learning results in an increase in 0.674 units of Management Innovation. The R square value is 0.454, which manifests that Market Learning causes a 45.4 percent change in Management Innovation. 54.6 percent change in Management Innovation is still undetermined, and the t-value is 13.321. The result exhibits that Market Learning has a positive and significant relationship with MI.

Table 5 - Market learning relation and Management Innovation

Hypothesis	β-Coefficient	R-square	t-value	p-value	Result
1. ML & MI	.674	.454	13.321	.000	Supported

Hypothesis 2: Market learning has a positive relation to knowledge integration.

The assumed hypothesis is supported as the p-value is 0.000, which is significantly lower than 0.05 degree, as manifested in table 6. The Standardized Coefficients β is 0.695, which manifests that an increase in 1 unit of Market Learning results in an increase in 0.695 units of Knowledge Integration. The R square value is 0.482, which manifests that an overall 48.2 percent change in Knowledge Integration is caused by Market Learning. 51.8 percent change in Knowledge Integration is still undetermined, and the t-value is 14.088. The result exhibits that Market Learning has a positive and significant relationship with KI.

Table 6 - Market learning relation and Knowledge Integration

Hypothesis	β-Coefficient	R-square	t-value	p-value	Result
2. ML & KI	.695	.482	14.088	.000	Supported

Hypothesis 3: Knowledge Integration is directly related to Management Innovation.

The assumed hypothesis is supported as the p-value is 0.000, which is significantly smaller than 0.05 degree, as exhibited in table 7. The Standardized Coefficients β is 0.653, which manifests that an increase in 1 unit of Knowledge Integration increases 0.653 units of Management Innovation. The R square value is 0.427, which manifests that Knowledge Integration causes 42.7 percent change in Management Innovation. 57.3 percent change in Management Innovation is still undetermined, and the t-value is 12.594. The result exhibits that Knowledge Integration has a positive and significant relationship with MI.

Table 7 - Knowledge Integration and Management Innovation

Hypothesis	β-Coefficient	R-square	t-value	p-value	Result
3. KI & MI	.653	.427	12.594	.000	Supported

Hypothesis 4: Knowledge Integration is mediating positive relation between Market Learning and Management Innovation.

The assumed hypothesis is supported as an indirect effect between ML and MI exists through Knowledge Integration; it is analyzed through Preacher and Hayes Analysis for mediation using model 4. The finding manifests that the indirect effect is .2367, which exhibits knowledge integration is taking ahead 23.67 percent impact of Market Learning to Management Innovation as manifested in table 8. The Upper Limit Confidence interval and Lower Limit Confidence interval do not contain 0, which means the mediation is intense. This suggests that the mediation effect exists, and the results are significant statistically.

Table 8 - Mediation Analysis

Hypothesis	Effect	p-value	LLCI	ULCI	Result
4. KI, ML & MI					
Total Effect	.6424	.000	.5473	.7374	
Direct Effect	.4057	.000	.2816	.5298	
Indirect Effect	.2367	.000	.1062	.3714	Supported

Discussion

Past research also proves that Innovation process of a firm can be improved by combining the existing and newly acquired market knowledge and knowledge integration can be done effectively when there are proper integration and operational mechanisms (Azadegan et al., 2008; Berggren et al., 2011; Lane et al., 2006; Martín-de Castro et al., 2011). The disruptive management models of successful organizations like HCL Technologies and Google have transpired the concept of management innovation in the modern dynamic business environment. This study speculates the role of market learning in the innovation of management practices of the organization. Market learning allows the inward flow of outside information and knowledge within the parameters of the organization (Kim & Atuahene-Gima, 2010). Market learning as a source of extrinsic knowledge plays a vital role in stimulating the management innovation process, creating possibilities for firms to discover a broader range of management approaches and methods. Thus, Market Learning and Management Innovation are directly related variables. Entrepreneurial organizations focus on market learning and actively implement knowledge integration in the technological and managerial practices that create value for the organization (Weerawardena, 2003). Therefore, Knowledge Integration enhances the process of Market Learning. In knowledge integration, a shared vision of the firm is created in the organizational context, which allows the transfer and processing of inside and outside knowledge (Cummings, 2004). This integration promotes the transmission of versatile data into a new format of integrated and original knowledge, supporting the innovation process (Salazar et al., 2012). Hence, we can say that knowledge integration and management innovation have a positive relationship. This discussion also supports the mediating role of knowledge integration between market learning and management innovation. Finally, we are able to say that market learning magnifies the impact of management innovation practices with complementary role of knowledge integration.

Conclusion

The results of this study are consistent with the assumed hypotheses. The findings will create value by combining market learning, management innovation, and knowledge integration. The incorporation of knowledge integration as a mediator is a new contribution to the existing literature as knowledge integration

contemplates market learning to augment the extent of management innovation. Sustainability of competitive advantage is crucial for the success of a firm, and management innovation accelerates this process. In the hospitality sector, managers tend to follow more unconventional approaches when organizational culture allows speculating the market changes and promotes the incorporation of knowledge among employees and managers at different levels. Thus, management style becomes more unorthodox and creates the right mix of practices and procedures evolving according to the firm's requirement. This model could help enhance employee participation, thus lead to a firm's productivity.

Limitations and Further Research

Every research encompasses a variant set of limitations, giving the idea of the researcher's boundaries. The same is the case with our analysis as it confines us within the scope of a limited topic. Prime limitations are the following:

1. The scope of this paper is bounded within the hospitality industry; hence, future research should induce our findings in other service sectors.
2. Also, it would be fascinating to incorporate the role of emotions as a moderator between knowledge integration and management innovation as emotions have a significant impact on the work behavior of employees (Luqman et al., 2020)
3. As we conducted our research in a developing country, researchers can empirically test this model in developed countries to measure the impact of economic conditions.

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Research Article

Employee Empowerment and Innovative Work Behavior: The Moderating Role of Leader-Member Exchange

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Purpose: This paper seeks to address the moderating effect of leader-member exchange on the link between employee empowerment and innovative work behavior.

Design/Methodology: The study draws on the causal-comparative research design, and employs paper-based self-administered questionnaires to gather data from a sample of 470 employees drawn from manufacturing firms in Kenya. This sample is part of a population of 9915 employees and has been narrowed down using Yamane's formula. The study employs stratified and simple random sampling techniques to constitute the required sample of employees.

Findings: The results indicate that employee empowerment and Leader-Member Exchange positively and significantly affect innovative work behavior. The results further reveal that Leader-member exchange significantly moderates the link between employee empowerment and innovative work behavior.

Practical Implication: The findings of this study provide an avenue through which managers of manufacturing firms can identify constructs that best explain innovative work behavior, especially during challenging times such as this time of Covid 19 pandemic. The results of this study provides managers with opportunities to come up with techniques, policies and strategies to improve relationship between employees and their supervisors for purposes of improved productivity, employee loyalty and reduced conflicts.

Originality/Value: The study makes a novel attempt to show the moderating influence of leader–member exchange in the context of employee empowerment and innovative work behavior in manufacturing firms in Kenya. Moreover, the study underscores the importance of leader member exchange in employees' innovative behavior, which is vital knowledge in tough times like the current uncertainty caused by the covid-19 pandemic.

Introduction

The manufacturing sector stands out as an essential pillar to the growth of Kenya's economy. As a result, it is recognized as one of the most critical sectors in the Big Four Agenda outlined by his Excellency, the president of the Republic of Kenya Hon. Uhuru Kenyatta (Ngugi, 2019). This is a four-point plan targeting food security, manufacturing (mainly focusing on job creation), affordable universal health care, and affordable housing which, the president believes that if leveraged, would improve the living standards of Kenyans, grow the economy and leave a lasting legacy. However, the Kenya Association of Manufacturers (KAM) and the Kenya Business Guide (KBG) have noted a significant drop in the manufacturing sector's contribution to the country's GDP, raising fears that the country could experience premature deindustrialization (KAM, 2018; KBG, 2018). Moreover, a study carried out by SYSPRO (vendor specializing in the provision of ERP and other advanced business software to mid-size producers and distributors), a global technology firm in partnership with Strathmore Business School points out several challenges that are holding back the Kenyan manufacturing sector and cites inability to run optimally as the bane of performance of most companies in the sector (Wangui, 2019).

Nevertheless, the culture of innovation among organizations is touted as one way through which the growth of Kenya's manufacturing firms can be guaranteed (Miano, 2019). While recognizing the significant steps that Kenya, as a country, is taking towards nurturing the innovative culture Miano (2019) concurs that acceleration of the country's growth, which as it is, still lies in its nascent stages is critical to the emerging competition. The extant literature demonstrates that adoption of a culture that is sensitive to the enhancement of innovativeness and creativity is indeed a sure way through which organizations can remain competitive (J. P. De Jong & Den Hartog, 2007).

The significance of innovativeness among manufacturing firms is further emphasized through the Deloitte report presented at the World Economic Forum, and which recognizes the role 'minds' as opposed to 'mines' are poised to play in the future of Africa's development (Deloitte, 2016). The report postulates and rightly so, that Africa is in possession of a valuable resource in terms of a higher percentage (60 percent) of a population aged under 35 years (African development bank report, 2014). Consequently, the continent stands a better chance to be propelled into a higher growth trajectory through innovative work behavior. Other scholars have made similar observations (Aghion, Boulanger, & Cohen, 2011).

Although a lot of interest is being shown towards innovations among entrepreneurs, investment in creativity and innovation, particularly in research and development, need not be taken for granted (Ndemo & Aiko, 2016). Investment in innovation among employees in the form of empowering them features prominently in the discourse on innovativeness among firms in areas such as correcting errors and re-designing work processes (Uzunbacak, 2015); managing innovative processes (Saray, Patache, & Ceran, 2017) and innovative work behavior (Alkhodary, 2016) among others.

Yet, the empowerment of employees is in itself not enough to spur innovation among employees. Interpersonal relationships and relationships nurtured between employees and their immediate leaders should not be underestimated. Scholars have increasingly demonstrated that leader-member exchanges enhance trust, respect, support, and loyalty and also facilitate the acquisition of innovative work behavior (Alsughayir, 2017; Bibi & Afsar, 2018; Tastan & Davoudi, 2015). Despite several policies being developed to guide innovativeness in organizations in Kenya, investment in leader-member exchange remains silent in most of these policies. This paper, therefore, seeks to address this gap by employing the theory that governs exchanges between leaders and their protégés to explore the quality of relationships nurtured between supervisors and employees in manufacturing firms in Kenya and how such relationships moderate the interconnection between empowered employees and their innovative work behavior (IWB).

Literature Review

The current study is embedded in the theory of innovation diffusion proposed by Everett Rogers in 1962 (Rogers, 2003) and leader-member exchange dyadic theory of leadership developed by (Dansereau Jr, Graen, & Haga, 1975; Van Breukelen, Schyns, & Le Blanc, 2006). The theory of innovation diffusion underscores the rationale upon which new ideas and technology can be infused in production in the event of varying conditions. It seeks to remind organizations on the importance of responsiveness to creativity and innovation in the wake of industry changes. Manufacturing firms in Kenya operate under varying conditions and often use different approaches to empower employees which make this theory critical to the current study. On the other hand, the leader-member exchanges theory postulates that the quality of exchange relationships nurtured between leaders and subordinates informs the kind of leadership exhibited. Consequently, exchanges could be of high quality, in which case they would be characterized by liking, trust and mutual respect or, of low quality and exemplified by suspicion, skepticism, hatred and antagonism among others.

Innovative Work Behavior (IWB)

The concept of IWB is best approached from the realm of knowledge economy where intangible assets get recognition for their role in organizational competitiveness under the presumption of 'doing more with less' (Crossan & Apaydin, 2010). It has been argued that employee innovation is reminiscent of organizations that are seeking high performance (Korzilius, Bücker, & Beerlage, 2017). In this context then, Riaz, Xu, and Hussain (2018) build on a previous definition by Scott and Bruce (1994) which, relates innovative behavior to generation, realization, and promotion of novel ideas in the organization among groups of employees or individual employees. J. P. De Jong and Den Hartog (2008) on the contrary adopt the definition which looks at IWB as a behavior elicited by an individual intending to initiate and introduce novel ideas, procedures, processes, and products that could ultimately be useful to the organization. They posit that unlike creativity, IWB has a more explicit applied component that comes up with mutual benefits.

Although many manufacturing industries have been operating in diverse sectors in Kenya, the agricultural sector accounts for better productivity and growth realized through innovations. As a result, the sector has been at the center of the innovation policies in Kenya (Ndemo & Aiko, 2016). The current study seeks to cover this gap by bringing on board other sectors in the manufacturing industry. To do so, the study first examines whether empowering employees relates directly to IWB in manufacturing firms from diverse sectors. Second, assuming that such a direct linkage exists, the study demonstrates the potential inherent in leader-member exchange (LMX) to moderate it. We, therefore, use the conceptual model displayed in Fig. 1.

Employee Empowerment and Innovative Work Behavior

Employee empowerment is a kind of strategy and philosophy that provides an employee with the opportunity to make decisions and take responsibility for their outcomes (Ndegwa, 2015). Existing literature supports the argument that employee empowerment sparks innovativeness (Uzunbacak, 2015). Moreover, it has also been associated with employee autonomy and self-belief (Wong Humborstad, Nerstad, & Dysvik, 2014). Alkhodary (2016) noted that employee empowerment was critical to employees' originality and idea fluency. Similarly, Abuzaid (2018) attributed strategic success to employee empowerment.

Most of the studies that have been undertaken in Kenya have zeroed in on examining how employee empowerment was significant in various firms. For instance, Ndegwa (2015) analyzed how employee empowerment-related to performance in commercial banks in Kenya. Odero, Egessa, and Oseno (2020) examined the influence of empowered employees on the performance of deposit-taking savings and credit cooperative organizations (SACCO's) in Kenya. Ibua (2017) explored the effect of empowered employees on the performance of public universities in Kenya. Busara (2016) investigated the role that employee empowerment plays on the performance of government procurement.

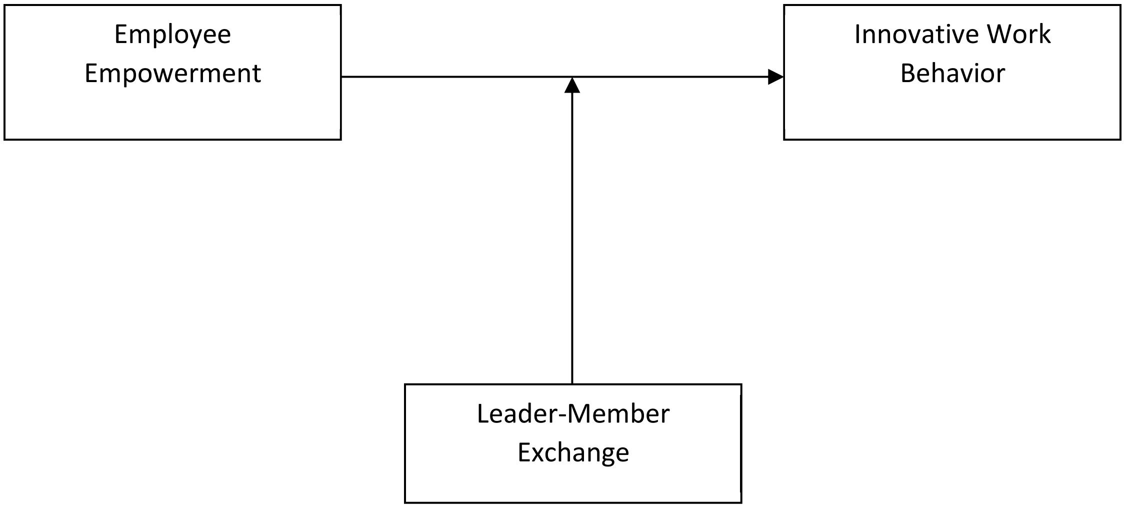

Figure 1 - Conceptual Model

Significantly, this array of studies conducted in Kenya is only relating employee empowerment with organizational performance. There is little or no evidence of whether employee empowerment has a direct influence on IWB. Given this, we, therefore, postulate that:

$H_0$1: *Innovative work behavior in manufacturing firms in Kenya is independent of employee empowerment.*

Moderating Role of Leader-Member Exchange

The ability to be innovative at work requires that workers engage in social processes when interacting with their co-workers and leaders (Carmeli & Schaubroeck, 2007). Indeed it has long been demonstrated that innovative behavior is a function of the work context (Carr, Schmidt, Ford, & DeShon, 2003). If a warm climate is nurtured between leaders and subordinates, it has been shown that creativity and innovation can be enhanced, culminating in individuals functioning at their highest level (Walumbwa, Wang, Wang, Schaubroeck, & Avolio, 2010).

Several studies highlight the moderating potential of leader-member exchange in various relationships. Lee, Scandura, Kim, Joshi, and Lee (2012), for instance, documented that LMX acts as a boundary condition in linking emotional intelligence with creativity. Hu and Zuo (2007) demonstrated that LMX moderates job insecurity and organizational commitment. Weigl et al. (2016) have also demonstrated that LMX moderates the link between burn out and emotional labor among clinical nurses. The moderating capacity of leader-member exchange has also been demonstrated in the bond between organizational commitment and job characteristics (Sullivan, 2017) and in the link between the behavior of citizens within organizations and authentic leadership (Stewart, 2012). If no documentation of the potential of LMX to moderate the interconnection between IWB and employee empowerment exists, we question whether it is viable and postulate that:

$H_0$2: *Leader-member exchange does not significantly moderate the relationship between employee empowerment and innovative work behavior in manufacturing firms in Kenya.*

Research Methodology

Study Design

The design adopted for this study was the causal-comparative design, which is ideal for cause-effect studies such as the current study (Saunders & Lewis, 2009). In examining how employee empowerment directly affects IWB, and how LMX moderates this direct effect, the current study fits in the cause-effect study category.

Sample

The population for the current study included 9915 employees working in manufacturing firms located in the industrial area of Nairobi City County. This was narrowed down to a sample of 470 employees on the strength of Yamane (1973) sample size formula and stratified across seven manufacturing sectors. Data used in the study were collected using a self-administered questionnaire comprising of four sections in line with the three study constructs and employees' background characteristics. Background characteristics related to employee gender, education, age, and experience. Employee gender was measured through the number of male and female respondents categorized as 0 and 1, respectively. The employee age was measured through the analysis of the five categories of ages, those below 20 years, 21-25, 26-30, 31-35, and those above 36 years. Education level was measured at certificate level, diploma level, Bachelor's degree, and postgraduate levels. Furthermore, the employee's experience was measured with the following experience ranges; less than five years, 5-10 years, 11-15 years, 16-20 years. Response scores were elicited on a 5-point Likert type scale scored as follows: 1-strongly disagree; 2-disagree; 3-neutral; 4-agree, 5-strongly agree.

Variable Measurement

Three variables were under consideration in the current study. J. De Jong and Den Hartog (2010) measurement scale were adopted albeit, with modifications to measure the four components of innovative work behavior, which included; idea generation, idea exploration, idea implementation, and championing. Eight items adopted from (Liden & Maslyn, 1998) scale were employed in measuring the four dimensions of LMX, namely; the contribution of exchange, professional respect, loyalty, and affect. A self-developed scale comprising 20 items and developed in line with suggestions by Petter, Byrnes, Choi, Fegan, and Miller (2002) measured the four dimensions of employee empowerment, namely; power, information, knowledge, and rewards.

Data Analysis

Data analysis targeted both inferential and descriptive statistics. Descriptive statistics focused on respondent's demographics and exploration of the prevailing leader-member exchange relationships in manufacturing firms under investigation. Inferential analysis was conducted using Hayes PROCESS Macro model 1 (Hayes, 2018). Under this approach, IWB was depicted as the criterion variable, employee empowerment as the predictor variable, and LMX as the moderating variable. The number of bootstrap samples was set at 10,000. Interactions were probed at a significance level of 0.05 with conditional values of negative one standard deviations (-1SD), mean (0 SD), and positive one standard deviations (+1 SD). The -1 SD value was customized as the 'low level,' 0 SD as the average level, and +1SD as the 'high level' of LMX.

Results

Out of the 470 questionnaires administered, 396 corresponding to 84.3 percent were returned and deemed ideal for the study basing on suggestions by Saldivar (2012). A list-wise deletion of missing values further reduced the sample from 396 to 384. The background characteristics of the study presented in Table 1 revealed the following: Most of the respondents were males (60.4%). Respondents were mostly of the Bachelor's degree level (47.7%) or diploma level (33.3%). Age-wise, most respondents ranged between 21 years of age and 35 years. Moreover, 204 had an experience of 1-5 years (53.1%).

Table 1: Demographic Background of the study

		Frequency	Percent
Gender	Male	232	60.4
	Female	152	39.6
	Total	**384**	**100**
Education	Certificate Level	43	11.2
	Diploma Level	128	33.3
	Bachelor's Degree	183	47.7
	Post-graduate	30	7.8
	Total	**384**	**100**
Age	Below 20 years	16	4.2
	21-25	116	30.2
	26-30	99	25.8
	31-35	96	25.0
	Above 36 years	57	14.8
	Total	**384**	**100**
Experience	1-5	204	53.1
	6-10	119	31
	11-15	36	9.4
	16-20	14	3.6
	Above 21 years	11	2.9
	Total	**384**	**100**

Source: Research Data (2020)

Table 2 presents the means, standard deviations, reliability, and correlation of general levels of all variables in the study. From the results, a significant correlation between employee empowerment, LMX, and Innovative behavior among employees was reported.

The findings presented in Table 2 show that Innovative work behavior leads with the highest mean of 4.07 (SD =.557). It is followed by Employee empowerment with an average of 3.67 (SD =.600), while LMX had the lowest average of 3.57 (SD = .700). Furthermore, the findings reveal that all variables had scale reliability above 0.8, with Employee empowerment having the highest Cronbach's Alpha of .887, followed by Innovative work behavior with .864, whereas LMX had the lowest score of .837. Finally, findings of the Correlation analysis show that both Employee empowerment and LMX have a strong linear relationship with innovative work behavior. Employee empowerment has the highest relationship with $r = .724$, $p < .01$, while LMX has the lowest but most important relationship with $r = .643$, $p < .01$. Furthermore, the findings show that LMX significant association with the empowerment of the employee, as shown by $r = .705$, $p<.01$.

Table 2: Results of Means, standard deviations, reliability and correlation of the study

Variable (n = 384)	M	SD	Reliability	Correlation		
Innovative work behavior	4.07	.559	.864	1		
Employee Empowerment	3.67	.600	.887	724	1	
LMX	3.57	.700	.837	.643**	.705**	1

Note: Correlation is significant at ** *p* <.01, (2-tailed), M= Mean, SD = Standard deviation, LMX= Leader Member Exchange

Hypothesis testing

Conditional Process analysis using Hayes (2018) Process Macro (Model 1) was used to test Hypotheses H1 and H2, as presented in Table 3. From the table, the following results are discerned. The overall Model explained

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40.3% of the total variance, with an R-square of 0.403, which was statistically significant at (F=85.645, p<0.000). Results indicate that employee empowerment has a direct and significant effect on IWB (b=.352, p<0.001) which show that for every 1 unit increase in employee empowerment, there was a 0.352 unit increase in IWB. The results further reveal that LMX has direct and significant effect on IWB (b = 0.225, p<0.001) showing that every 1 unit increase in LMX there was a 0.225 increase in IWB. Mostly, the interaction of LMX on the link between employee empowerment and IWB shows a significant effect (b=-.117, CI=[-.202,-031]). All the control variables were included, and results indicate that all covariates were not significant in the current study.

Table 3: Summary of multiples regression Analysis

Variables	b	SE	t	p	LLCI	ULCI
Constant	4.101	.025	167.408	.000	4.0531	4.150
Empowerment	.352***	.044	7.982	.000	.265	.439
LMX	.225***	.038	5.968	.000	.150	.299
Interaction	-.117**	.044	-2.671	.007	-.202	-.031
Gender	.004	.082	.047	.962	-.158	.166
Education	-.005	.052	-.089	.929	-.106	.097
Age	-.041	.043	-.951	.342	-.124	.043
Experience	-.013	.048	-.267	.789	-.107	.081
R^2	.403					
F	85.645***					

N=384, Note***P<0.001, **P<0.01, LMX =Leader-Member Exchange

The nature is interaction is shown in Figure 2. The results clearly show that investment in LMX reduces the amount required to empower employees. For low LMX, employee empowerment is very critical, as depicted by the high slope. However, at high LMX, the slope for employee empowerment on IWB reduces, indicating that energies spent on employee empowerment can be reduced in favor of LMX (see Fig 2).

Figure 2 - Nature of interaction between empowerment and LMX

Discussion

The current study revealed that employees in manufacturing firms in Kenya enjoy cordial relationships with their immediate leaders who, in this case, are supervisors. Moreover, employee empowerment directly

influences innovative work behavior. However, this influence is moderated by the nature of relationships that exists between employees and their supervisors.

The findings of the current study have important implications for existing theory on innovative work behavior. First and foremost, the study is a novel attempt to show the moderating influence of leader-member exchange in the context of employee empowerment and innovative work behavior in manufacturing firms in Kenya. Indeed existing theory mainly focuses on the direct effects of employee empowerment or leader-member exchange on organizational performance (Busara, 2016; Ibua, 2017; Ndegwa, 2015; Odero et al., 2020). The Hayes Macro Process Approach adopted in the study allows for an elaborate exploration of the moderation potential by not only concentrating on the overall Model, predictors, and the interaction but also giving the moderation plot that allows visualization of the employee empowerment slopes at varying levels of LMX.

In finding that employees and their leaders in manufacturing firms in Kenya enjoy cordial relationships, the study emphasizes and supports previous arguments which have hitherto pointed out that the quality of employee-supervisor relationship enhances job satisfaction, job performance, employee engagement and employee commitment among others (Birkenmeier & Sanséau, 2016; Radebe & Dhurup, 2017). The study confirms that manufacturing firms in the industrial area have the desire to invest in leader-member relationships.

The study also found out that employee empowerment impacts positively on IWB among employees working in manufacturing firms in Kenya. This finding adds to the growing body of literature on employee empowerment, which has previously only focused on employee empowerment and organizational performance (Busara, 2016; Ibua, 2017). Moreover, the study established that LMX moderates the interaction between employee empowerment and IWB, with the slope of employee empowerment being more significant at low levels of LMX and smaller at high levels. This finding confirms that when the relationship between employees and their immediate leaders is good, firms are bound to save on investments made towards empowering employees. Indeed, LMX gives the employees a real feeling of empowerment, which has often been overlooked (Nash, 2019).

Managerial Implications

The findings reported in the current study are essential in the sense that they underscore the value of leader-member exchange relationships in the desire to enhance innovative work behavior. This knowledge is particularly relevant to manufacturing industry stakeholders and managers, especially in these difficult times of COVID 19. By investing in LMX relationships between employees and supervisors, manufacturing firms are bound to improve productivity, employee loyalty, and reduce conflicts. It has, for instance, been shown that firms that have invested in strong employment relations have seen their productivity increase, have also maintained a loyal workforce, and has seen a reduction in conflicts (O'Brien, 2014).

Moreover, through the study findings, individuals charged with leadership positions are made aware of the traits such as Candor (Honesty without ambiguity), empathy, flexibility and adaptability, active listening, and humility which are reckoned to be especially relevant in this COVID 19 period (Brownlee, 2020).

Limitations

The main limitation of the current study lies in the use of data obtained only from manufacturing firms in the industrial area of Nairobi City County. Organizational structures in these firms are bound to differ from those of other locations since there is cut-throat competition among the firms in the study location, which could be the source of enhanced IWB. Secondly, by relying wholly on questionnaires administered to employees only, the study fails to account for the views of supervisors and managerial staff in general. Third, the current study uses PROCESS, which although being quite useful in moderation, does not allow for the use of latent variables to control for measurement error and does not test interactions with a categorical variable (Schwarzkopf, 2015).

Conclusion

The study represented an explicit attempt to understand the role LMX has to play in spurring up IWB in manufacturing firms in Kenya. Although employee empowerment was found to have a direct effect on IWB, the study presented evidence to show that LMX complements to the contributions made by employee empowerment. Consequently, manufacturing firms can relax investment in employee empowerment by supporting and creating atmospheres that enhance employee-supervisor relationships. Nevertheless, for more representation, future studies should look to widen the geographical scope of the study by including manufacturing firms from other Counties. Moreover, future studies should focus on triangulating data collection to bring onboard views of other stakeholders.

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Research Article

Evaluating the Heterogeneous Effect of Firm Risk on Firm Value

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Abstract

Purpose- This paper aims to investigate the effect of firm risk on the firm value to see how the firm value is changing when the risk level is changed. Our result indicates that a higher level of risk can reduce firm value.

Design/Methodology- We apply a Bayesian causal technique for a sample data set of US public firms. The causal approach helps us to focus on the reliable and unbiased results instead of the association-based findings.

Findings- The results show a negative effect of risk on the firms' value for the sample data. However, we investigate the potential effect of the risk across the distribution of the firm value. We witness the more substantial effect of risk on firms with a higher value.

Practical Implications- Helps firms to evaluate their risk and its effect, so they can adjust their decisions and take actions to reduce the undesired effects of firm risk.

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Introduction

The firm value and firm risk have been widely investigated in the finance literature. It is so essential for each firm to monitor its value and investigate the different factors that can influence the firm value. Firm risk can have different impacts on various aspects of the firms. These effects have been studied in various contexts and resulted in two groups of research. The leading group of studies supports the risk-return tradeoff theory, which is also known as the fundamental theory in finance literature. Based on this theory, there is a positive association between the risk and return, meaning that the higher return should be expected to take higher risks. This approach is more vital for the stock portfolio than for the firms. However, another group of related studies revealed a negative correlation between these two variables. Bowman (1980)found the negative association between the risk and return, which has been named Bowman's paradox. After Bowman, a considerable amount of studies published the same results and supported the paradox. Related research showed that taking a risk may result in a lower return instead of a premium. This could happen because of the poor performance of decision-makers to impact the firms negatively in terms of risk and return at the same time.

There are so many studies that examined the relationship between the risk and return for firms. The related literature provides the mixed finding of positive and negative effects (Bowman, 1980; Chari, David, Duru, & Zhao, 2019; Faraji, 2020; Faraji & Fleischhacker, 2020; Yang, Riepe, Moser, Pull, & Terjesen, 2019). Therefore, the effect of risk on firm value or performance is not completely clear. A tiny fraction of the related research focuses on finding the more concrete results by deploying the causal approach (Faraji, 2020; Faraji & Fleischhacker, 2020). Based on this group of research, the reason for mixed findings is the correlation-based models, which are unable to tease out the accurate and stable magnitude of the effects. The causal approach can extract the unbiased effect by applying causal models (Hernán & Robins, 2010). This study is motivated based on the approach that has been used by (Faraji & Fleischhacker, 2020). They showed that when the main question is not correlation-based, then Bayesian causal models can provide reliable and concrete results for observational studies. They are among the first researchers that consider the Bayesian approach for causal model to remove the spurious associations for observational financial data. We are considering Bayesian causal models for financial data instead of frequentist association-based models to provide more reliable and less biased results; all these goals have been considered and applied by (Faraji & Fleischhacker, 2020). They provide a comprehensive study to overcome the limitation of the related studies. Following their approach, we extend this work with causal inference to examine the effect of risk on firm value.

The rest of this paper includes the following sections, the next section discusses a literature review about firm risk and firm value, following with a review of the causal inference for observational studies. Then the research method section, the empirical results, are provided with a description of the data. The last section is about the conclusion and limitations of the present paper.

Literature Review

The relationship between firm risk with the performance or firm value has been widely studied in financial literature. The risk-adjusted return approach is based on the positive correlation between risk and return. Applying the risk-adjusted return helps to examine the amount of risk that should be taken to gain the desired level of return. Different measures such as the Sharpe Ratio, Appraisal Ratio, and Treynor Ratio investigate how the risk and return change together (Faraji, 2020; Lee & Li, 2012; Sharpe, 1966). Also, the positive relationship has been found between risk and expected return, which means that managers should choose risk investment only if it can maximize the stakeholder wealth (Barberis, Huang, & Santos, 2001; Chari et al., 2019; Merton, 1987).

In contrast, Bowman's risk-return paradox shows the negative relationship between risk and return. Different factors, such as poor management or personal benefits, may lead to making decisions that increase the risk and reduce the value for firms (Bowman, 1980). Indeed, managers impose the risk-discount by taking a higher risk for the same or even lower level of return. According to Ang, Hodrick, Xing, and Zhang (2006)) risk and firm return have a negative association. One way to explain such this paradox is through the agency problem (Chari et al., 2019). Risk-averse managers only take higher risks if they can gain a higher return. However, the empirical results show that career concerns may push managers to make high risk and value reducing decisions. Also, the solution to avoid such decisions is to have more robust corporate governance (Chari et al., 2019). Also, another group of research supports Bowman's paradox differently by providing empirical results, wherein it shows increasing return and reducing risk (Yang et al., 2019). This effect can be seen in firms with related business segments; however, in firms with unrelated business segments, it is more likely to observe the positive association between risk and return (Bettis & Hall, 1982). Indeed, the synergy among the different segments can help the firms to reduce their cost and risk. Economic of scale, shared resources, managerial skills, and information are among the key factors that can empower the firms (Yang et al., 2019). The relationship between risk and return can be explained well in the context of diversification (Faraji & Fleischhacker, 2020).

Many studies tried to investigate the potential role of other firms' aspects in the relationship between risk and return. As mentioned before, the corporate governance variables may play a mediating role and result in a suppressed mediating effect (Chang, Yu, & Hung, 2015). Also, the role of various financial variables can be examined by applying different measures to evaluate firm risk and value. They are using cash flow volatility as a risk measure that shows a negative association between firm value and risk (Rountree, Weston, & Allayannis, 2008). Another research reports the negative association between cash flow volatility and firm value, which is measured by Tobin's Q (Chi & Su, 2017). Also, it has been reported that this association depends on the firm investment opportunities, firm size, and the correlation among business segments (Chi & Su, 2017; Pástor & Pietro, 2003) leads to a negative association between firm valuation and firm's profitability when the firm age increases. Shin and Stulz (2000) provided the different relationships between firm value using Tobin's Q with systematic and unsystematic risk. They suggested the firm value increases with the systematic risk but decreased with the unsystematic risk. Also, the effect on the female board on Norwegian firms' risk and performance has been studied in a causal context, by using Tobin's Q and real risk as to the measures for firm value and risk (Yang et al., 2019). In this study, the difference-in-difference approach has been used to find the unbiased and negative effect of female directors on firm performance and risk. In another study which focuses on stability of the firm's risk-return association across the market trends (Gupta & Pathak, 2018). Their sample data includes firms form developed and emerging countries. The results showed that the paradoxical and positive relationship between risk and return, however, they found the firms in emerging countries riskier than the developed countries.

Following the related literature, we use Tobin's Q to measure the firm value in this paper (e.g., (Chi & Su, 2017; Shin & Stulz; Yang et al., 2019). Which is the market value of equity plus debt divided by assets? Also, we measure the firm risk with absolute risk, which is the annual standard deviation of firms' daily stock return (Lee & Li, 2012; Yang et al., 2019). This is a well-established measurement of total firm risk and can be estimated as the sum of the squared daily log returns when the mean value of the daily log returns is subtracted. This risk measure provides a complete picture by capturing the full risk for the firms as well as the investors (Yang et al., 2019).

Causal Inference for Observational Study

By reviewing the related research, the mixed results are based on the association. However, the results based on the correlation can be biased for observational data (Faraji, 2020). We deploy a causal inference approach to find the more accurate effect of the variables. It is required to apply a causal model instead of association-based

models to remove the undesired association, such as the confounding effect. The difficulty of causal inference is related to the data limitation, which refers to the missing potential outcomes in causal studies. In observational studies, only one outcome is observed for each individual, and the others are not observed. However, with a binary exposure, both potential outcomes are required to find the effect of exposure on the outcome of interest. To overcome this limitation, causal models are helpful in finding the average effect of the variables by considering the effect across the population instead of individuals (Rubin, 2005).

In causal inference, valid results depend on holding the causal assumptions. Without these assumptions, we are not able to interpret the results in a causal context. These assumptions are Positivity, Consistency, and exchangeability (Hernán & Robins, 2010). Positivity refers to having a positive probability of receiving all the exposure levels for individuals. Defining an apparent intervention lead to holding the consistency assumption. The last assumption or exchangeability means that the information about the intervention cannot help to estimate the outcome variable. Indeed, for intervention levels, the intervention and outcomes are independent (Hernán & Robins, 2010).

Following Hernán and Robins (2010), we assume the outcome as Y, intervention as A, and other variables that can result in confounding bias as L. Then the potential outcomes for each individual i in the sample population are Y_i^1 *and* Y_i^0, which represent the potential outcome with assigned intervention and with no intervention assigned respectively. The individual effect in the causal context would be $Y_i^1 - Y_i^0$, However, as mentioned before only one of these outcomes is observed. Consequently, finding the effect size at individual level or $Y_i^1 - Y_i^0$ is impossible. Finding the average effect for the population can handle this problem (Rubin, 2005).

The average effect can be calculated based on equation (1):

$$E(Y_i^1 - Y_i^0) = E(Y_i^1) - E(Y_i^0) \qquad (1)$$

By estimating these values, we can find the average effect as:

$$\mathrm{E}(\mathrm{Y_i}|\mathrm{A}=1) - \mathrm{E}(\mathrm{Y_i}|\mathrm{A}=0) \qquad (2)$$

If there is any confounding bias, then we should find the average effect given the confounders variables as:

$$\text{Average Effect } = E(Y_i|A=1, L) - E(Y_i|A=0, L) \qquad (3)$$

Following Faraji and Fleischhacker (2020), we use a causal model to examine the presence of a causal relationship between risk and firm value.

Research Method and Data

Sample Data

Different financial variables are considered as control variables in associational studies. In the current paper, we look for the confounding variables to remove their associated bias. We consider the age, size, growth opportunity, and leverage as confounders. The causal model helps to remove the confounding bias to drive the more accurate effect of the risk on firm value. As mentioned before, the continuous outcome is a firm value measured by Tobin's Q, which is the market-based measure. Also, the intervention or risk here is measured as the annual standard deviation of firm stock return, which can be calculated as the variance of the sum of the squared of subtracting the mean value of daily log return form the daily log returns. Many studies consider a binary or multi-level measure for risk, such as the famous Altman Z-Score (Altman, 1968). Faraji (2020) consider the distress risk as a binary variable in a causal study. Following the related literature, we assume risk as a binary variable with a high and low level of risk for firms. Indeed, we consider the firms with lower risk

than the median risk value as firms with low risk and firms with a higher risk than the median value as high-risk firms. As a result, we suggest having a binary exposure to examine the effect of risk. The data are extracted from CRSP and Compustat data sources. The data covers 2018 for around 2800 US public firms. The next table provides a summary of descriptive statistics for the variables of this study.

Table 1 - Descriptive statistics of the variables

Variable	Mean	Sd	Median
Age	19.05	15.61	18.00
Total Assets	10147.2	37087.35	1198.6
Total Liabilities	6401.5	21985.53	589.1
Debt Ratio	0.5681	0.765	0.5402
Size	6.515	1.91	6.987
Growth Opportunity	0.0742	0.39	0.00
Tobin's Q	1.074	5.29	0.688
Risk	0.0264	0.018	0.01987

Bayesian Statistical Model

Different causal models can help us to find the average effect for the population with observational data. In this study, we use g-formula to find the average effect. We provide a quick summary of the g-formula here, but we refer the reader to Hernán and Robins (2010) and Faraji and Fleischhacker (2020) for more details. Under the three assumptions of consistency, positivity, and exchangeability, the g-formula helps to estimate the missing potential outcomes to sample the counterfactual means. Different steps are required in this model to be taken to estimate the parameter of interest or average effect. First, the parameters' estimations should be obtained to find $E(Y^1)$ and $E(Y^0)$ by the following equation:

$$\widehat{\mathrm{E}}(\mathrm{Y}^{\mathrm{a}}) = \sum_{l} \widehat{\mathrm{E}}[\mathrm{Y}|\mathrm{A} = \mathrm{a}, \mathrm{L} = \mathrm{l}]\ \mathrm{Pr}[\mathrm{L}=\mathrm{l}] \qquad (4)$$

Where a represents a binary exposure (Risk), Y is the potential outcome (Firm value), and L can be a single or a vector of potential confounders. Then the average effect is calculated by:

$$\text{Average Effect} = \widehat{\mathrm{E}}(\tilde{\mathrm{y}}^{\mathrm{a}=1}) - \widehat{\mathrm{E}}(\tilde{\mathrm{y}}^{\mathrm{a}=0}) \qquad (5)$$

Here, we use a Bayesian version of the causal technique to drive the sample of the parameters to estimate the counterfactual means. We consider a normal distribution for the firm value as a continuous outcome with risk as a binary intervention.

$$\text{Firm Value (Y)} \sim \text{F (Risk (A), Size } (\mathrm{L}_1)\text{ , Age } (\mathrm{L}_2)\text{, Debt Ratio } (\mathrm{L}_3)\text{, Growth Opportunity } (\mathrm{L}_4))$$

$$\text{Firm Value } (Y) \sim Normal\ (\mu, \sigma)$$

$$\mu = \alpha_0 + \alpha_a A + \alpha_1 L_1 + \alpha_2 L_2 + \alpha_3 L_3 + \alpha_4 L_4$$

We use weakly informative prior information for the parameters:

$$\alpha_a, \alpha_1, \ldots, \alpha_4 \sim cauchy\ (0, 2.5)$$

$$\alpha_0 \sim cauchy\ (0, 10)$$

$$\sigma \sim cauchy\ (0, 1)$$

Then the average treatment effect of diversification on the outcome is the difference between the mean of these two groups of high risk and low-risk potential outcomes.

$$\tilde{y}^{a=1} \sim Normal(\widehat{\alpha_0} + \widehat{\alpha_a} A + \widehat{\alpha_1} L_1 + \widehat{\alpha_2} L_2 + \widehat{\alpha_3} L_3 + \widehat{\alpha_4} L_4, \hat{\sigma})$$

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$$\tilde{y}^{a=0} \sim Normal(\widehat{\beta_0} + \hat{\alpha}_1 L_1 + \hat{\alpha}_2 L_2 + \hat{\alpha}_3 L_3 + \hat{\alpha}_4 L_4, \hat{\sigma})$$

Results

The sample draws from the hyperparameters are the output of our statistical models, then we should find the posterior predictive of the counterfactual outcomes by using them. The next table gives a summary of the hyperparameters estimation.

Table 2 - Summary of hyperparameter estimation

Parameter	mean	sd	2.5%	25%	50%	75%	97.5%
α_1	0.66	10.40	-19.36	-6.26	0.51	7.68	21.37
α_2	-0.65	0.05	-0.75	-0.69	-0.65	-0.61	-0.55
α_3	0.11	0.05	0.02	0.07	0.11	0.14	0.20
α_4	-0.01	0.05	-0.11	-0.05	-0.01	0.02	0.08

Then the average effect can be determined using equation (5). The following figure illustrates the distribution of the average effect for the exposure.

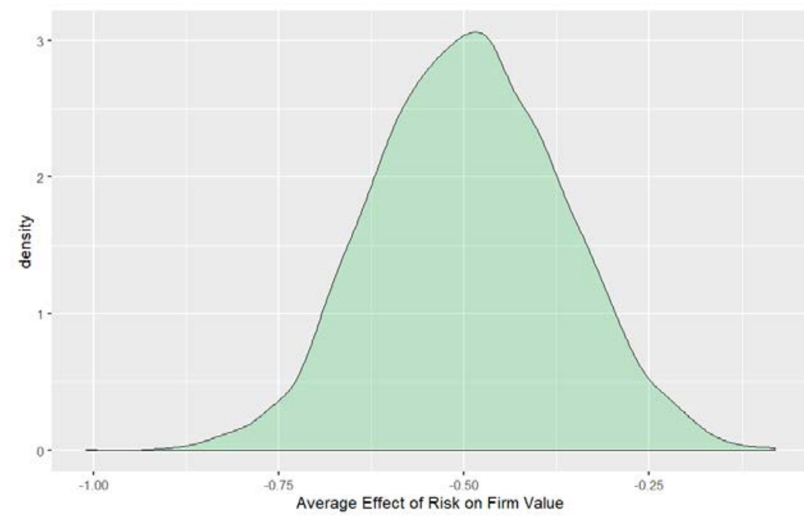

Figure 1 - Average Effect of Risk on Firm Value

According to the figure (1), the negative values across the distribution of effect shows the negative effect of risk on the firm value, which indicates that the firms with higher risk experience the lower value, while firms with lower risk having higher firm value. This means that risk is negatively associated with firm value but after removing the selection bias, confounding bias, and mediating effects, there is still a negative causal effect between them. These results support the Bowman's paradox with a causal approach.

We examined the effect of risk on the firms' value by considering low-risk firms and high-risk firms. Providing an average effect can be helpful when the effect is similar across the population. However, instead of summarizing all information in just one number, we can consider the effect across the outcome distribution. This approach can provide more information about the potential variation of effect distribution. The quantile treatment effect (QTE) shows the heterogeneous effect. The quantile approach investigates the effect for different quantiles and tails instead of the mean value (Bitler, Gelbach, & Hoynes, 2006; Koenker, 2005). This approach is useful when the effect in different quantiles are not similar to the average effect. As the average effect is more based on the parametric regression models, QTE deploys quantile regressions to find the effects.

Indeed, QTE finds the difference between the distributions of potential outcomes based on the inverse cumulative distribution functions for the quantiles (Koenker, 2005). The QTE can be defined as follows in a simple way:

$$QTE_q = F^{-1}_{y^{a=0}}(q) - F^{-1}_{y^{a=0}}(q) \qquad (6)$$

As the second research question, we investigate the potential heterogeneous effect of the risk on firm value. The next table shows the distribution of effect.

Table 3 - QTE of Risk on Firm Value

Quantile	QTE	Std. Error
0.05	-0.018	0.000
0.10	-0.017	0.000
0.15	-0.006	0.000
0.20	-0.017	0.000
0.25	-0.011	0.000
0.30	-0.012	0.000
0.35	-0.006	0.000
0.40	-0.001	0.000
0.45	-0.010	0.000
0.50	-0.006	0.000
0.55	-0.011	0.000
0.60	-0.012	0.000
0.65	-0.011	0.000
0.70	-0.044	0.000
0.75	-0.179	0.000
0.80	-0.811	0.000
0.85	-0.583	0.000
0.90	-0.934	0.000
0.95	-1.376	0.000

The results for the quantile effect are consistent with the distribution of average effect. Table 3 shows the negative effect on all quantiles, which means that higher risk leads to a lower value for firms. However, the heterogeneous effect would get clear in figure 2.

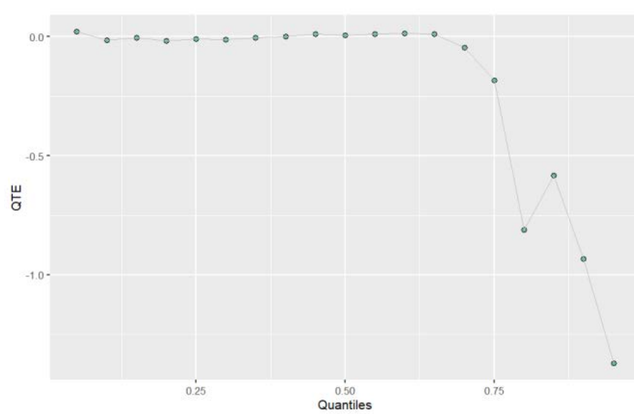

Figure 2 - QTE of Risk on Firm Value

According to the figure (2), while the effect of risk on firm value is almost in the same range from 5% quantile to 70% quantile, it decreases dramatically for the higher quantiles. This figure illustrates the heterogeneous effect sizes. This shows that only considering the average effect can provide a limited picture of the results.

Extending the study with quantile analysis in a simple framework can enable decision-makers and other researchers to examine the detailed information about the effect of risk on the firm value and adjust their decisions accordingly.

Conclusion:

In this study, we examine the causal effect of firm risk on the firm value measured by Tobin's Q for a sample of US public firms. We start with the average effect to see how the value of a risky firm can be impacted by the risk compared with fewer risk firms. The results show that risky high firms suffer from lower firm value. However, firms that experience a low level of total risk are experiencing a less negative effect on their values. This result supports the Bowman's paradox in some way as having a negative relationship between the firm risk and value. Also, we consider the potential heterogeneity for this effect across the distribution of firm values. The results provide more details about the heterogynous effect of the fire risk. It is so interesting to see that for firms at higher quantiles experience a more substantial effect than the firm in lower quantiles. Also, there are some limitations to this study. We suggest investigating more confounders and cover more years in the study for future studies.

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Research Article

Technology Management for Accelerated Recovery during COVID-19: A Data-Driven Machine Learning Approach

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Objective- The research looks forward to extracting strategies for accelerated recovery during the ongoing Covid-19 pandemic.

Design - Research design considers quantitative methodology and evaluates significant factors from 170 countries to deploy supervised and unsupervised Machine Learning techniques to generate non-trivial predictions.

Findings - Findings presented by the research reflect on data-driven observation applicable at the macro level and provide healthcare-oriented insights for governing authorities.

Policy Implications - Research provides interpretability of Machine Learning models regarding several aspects of the pandemic that can be leveraged for optimizing treatment protocols.

Originality - Research makes use of curated near-time data to identify significant correlations keeping emerging economies at the center stage. Considering the current state of clinical trial research reflects on parallel non-clinical strategies to co-exist with the Coronavirus.

Introduction

The discovery of Acute Respiratory Syndrome Coronavirus-2 (also known as Covid-19) as a deadly virus has put the globe on high alert. With a high infection rate and rising death toll, it has changed the way we live in society. It is beyond doubt that Coronavirus has caused massive economic distress around the world, leading to business interruptions and regional shutdowns (Martin et al., 2020a). The negative impact of Covid-19 on the economy is visible on the disruption of the supply chain and extends to stumbling socio-economic activities (Mhalla, 2020; Phillipson et al., 2020). The associated uncertainty of the pandemic is not only limited to the economic aspect but also increasing the psychological distress of people (Silva Junior et al., 2020).

As scientists are striving to contain the virus, it has become essential to adopt an approach that can take calculated risk to bring the situation to normalcy. While health professionals denounced the certification of the Russian Covid-19 vaccine as premature, as of now, social distancing appears to be the most effective measure for combating the pandemic (Mahase, 2020). Social distancing may work in high-income countries; however, low-income countries may not enjoy such benefits. On the contrary, the limitation posed due to lockdown in underdeveloped nations may lead to deprivation of people and a steep decline in the economy. This fact can make social distancing reflect poorly and make emerging countries vulnerable, and hence the exploration of alternative strategies appears to be a need of time (Barnett-Howell & Mobarak, 2020).

These alternative strategies can be drawn with the help of a technology called Artificial Intelligence (A.I.). Artificial Intelligence is viewed as a revolution in the current era, and it possesses an immense application in several areas, including healthcare. Machine Learning (ML) is the branch of Artificial Intelligence that can solve real-life problems by learning from data rather than being explicitly programmed (Saeb et al., 2016). Such digital transformation presents an opportunity to address issues across multiple facets of healthcare and administration using Machine Learning models (Feldman et al., 2017). While we are exposed to the Covid-19 pandemic, it presents an ideal scenario where we can exploit a digital transformation for the immediate benefits of society.

Considering the current state of a pandemic, it has become necessary to seek support from areas such as statistics and computer science. Accordingly, research makes use of state-of-the-art technology to extract an accelerated recovery plan with a data-driven approach. Researchers can deploy Machine Learning in the healthcare sector to predict future possibilities and propose effective strategies to deal with the Covid-19 outbreak. Based on the predictions from Machine Learning models, administrators can focus on planning and decision making during the pandemic (Madurai Elavarasan & Pugazhendhi, 2020).

The proposed research looks forward to fulfilling the same using data aggregated from the nations that have unfortunately been subjected to the ongoing pandemic. Research prominently demonstrates that Machine Learning can be used to discover interesting patterns and support sound decision-making. With efficient technology management, the study draws parallel plans to co-exist with Covid-19 while clinical trials await approval.

Literature Review

Impact of Coronavirus

Since it first appeared, Covid-19 has turned into a life-threatening pandemic that has pushed global health and socio-economic activities to the breaking point. A model developed to evaluate the socio-economic impact of pandemic estimates the negative effect of social-distancing on household income, savings, consumption, and poverty (Martin et al., 2020b). It is expected that the emerging world, including low and middle-income countries, will undergo more significant concerns during an ongoing pandemic (Klinger et al., 2020).

Countries at present are trying to inhibit the spread of the Coronavirus by adopting various strategies. While a lockdown can be an effective strategy of social distancing and successful in tackling the rapid spread of the infectious Covid-19 virus, it can also have a negative impact on society (Zhang et al., 2020). This fact is in agreement with research manifested in China by Zhu et al. (2020), where people experienced enormous psychological impact due to the pandemic.

Associated Factors

Prior research has established that the odds of death due to the Covid-19 infection increases along with age (Talukder et al., 2019). The study further elaborated on the types of diseases like hypertension, diabetes, and cardiovascular (referred to as comorbidities) that have a significant direct impact on infected patients. Apart from age and existing health conditions, there are a number of factors that can affect the recovery of Covid-19 patients. According to Livadiotis (2020), the statistical analysis of the impact of environmental temperature on Covid-19 patients suggests a negative correlation on the growth rate of infected cases. It has been suggested that Bacillus Calmette-Guérin (BCG) vaccination may also have a protective effect on the Covid-19 mortality rate. The data from publicly available resources also indicate that both Covid-19 incidences and deaths are associated with regional BCG vaccination policies. However, as per Miyasaka (2020), if BCG vaccination does contribute to lower Covid-19 mortality, it is not the only factor. The presented study looks for such associations in a systematic manner.

Another independent research by Klinger et al. (2020) concluded that that the inverse correlation with BCG vaccine administration and the validated role of the young population in the spread of Covid-19 calls for revisiting the BCG immunization policies. It must be noted that BCG vaccination is routine and near-universal in many low and middle-income countries. Data suggests that many countries in Asia, the Gulf, and Africa have maintained a flat mortality rate that can be correlated with the BCG vaccination policies (Debnath et al., 2020; Gursel & Gursel, 2020).

Recent studies have observed the dietary patterns where the ability of curcumin (a type of spice) has been found to have an inhibitory potential against different types of viral infections, making it a fit for resisting the coronavirus infection (Zahedipour et al., 2020). As per the guidance provided by Rozenfeld et al. (2020), the research has also identified additional factors associated with Covid-19. Considering lifestyle choices, the current study further explores associations with smoking as well as drinking habits (Chodkiewicz et al., 2020; Reddy et al., 2020; Sidor & Rzymski, 2020). Further, building on observations made by other studies, the proposed research attempts to re-confirm relationships among factors such as population density and pollution index (Contini & Costabile, 2020; Rashed et al., 2020; Rocklöv & Sjödin, 2020).

Treatment of Coronavirus

According to Jean & Hsueh (2020), several countries are working on medical trials that may deliver potentially applicable solutions to handle patients with various levels of Covid-19 infections. Although the Russian government has endorsed a Covid-19 vaccine - Sputnik V - it followed only a limited trial with no published results (Mahase, 2020).

Researchers believe that many of the reviewed trials lack the robust methodology required to make a sound conclusion (Sethi & Bach, 2020). Their study also suggests, these therapeutics still need a considerable level of investigation to establish efficacy and determine adverse effect profiles. Arguably, there is no valid confirmation of well-designed randomized and completed controlled studies for Covid-19 therapy.

Presented Challenges

At the same time, the existing set of drugs have been deemed as promising candidates for controlling Covid-19. These drugs have specific safety profiles. Although drug re-purposing is an essential step against the fight with Coronavirus, it may require caution. As a number of clinical trials that are underway, it is safe to assume that their results might help us defeat Covid-19, but it is likely to take a considerable amount of time (Scavone et al., 2020).

The evidence further indicates that more data is required to determine whether any therapeutic agent has strong efficacy in the treatment of Covid-19. While society is being subjected to Coronavirus's fury and working to develop an effective cure, we need to be aware that human-to-human virus spread is skyrocketing. It may result in an exponential rise of Covid-19 cases, and a sheer number of infected people can be overwhelming for populous nations. This presents a challenge to humanity in terms of limited information, limited time, and increased infection rate.

Application of Machine Learning

The above considerations in dealing with Coronavirus pave a way to address concerns using Artificial Intelligence as a method of choice. The transformative potential of Machine Learning in healthcare supports the prediction made by Alan Turing (1950) that 'machine intelligence' will have a pervasive role within our society (Ashrafian et al., 2015).

As per Tan et al. (2020), the evolution of deep learning mechanism as a sub-discipline of Machine Learning requires minimal user input and demonstrates the tremendous potential to identify patterns. The patterns retrieved using a computing algorithm can facilitate healthcare interventions as a powerful approach. (Ashrafian & Darzi, 2018; Saria et al., 2018) Machine Learning guided outcomes can offer new inroads through enhanced health-related screening (Goshen et al., 2018). Such digital transformation can help governing bodies to determine the applicability of the Machine Learning models and discover trends that are related to Covid-19. The most prominent contribution of A.I.to health policy knowledge currently resides within the application of ML to large, population-level datasets, as presented in current research.

Recommended Strategies

The pandemic originated due to Coronavirus is going to have a long-lasting global impact. It is expected that the effect of this pandemic would harshly reflect on our lives and reverberate for some time to come. Based on the review of literature, the presented research works towards a new line of research, keeping in mind that society may not be able to sustain the restriction posed by Covid-19 for too long. Without effective treatment protocol, the placement of cities in 'lockdown' can affect economies on a multi-lateral level, including both social and economic standpoints. Every country cannot afford extended lockdowns as it may affect people with limited financial means, and hence, the best approach includes a transition to live with Coronavirus.

Considering the relationships between the factors that caused the virulence of the respiratory disease, the measures are needed to be placed to control the pandemic. Also, the impact associated with the disease is necessary to be understood scientifically. Thus, the detection and management of the Covid-19 can become increasingly dependent upon the predictive capabilities of the technological backbone (Allam & Jones, 2020).

In the absence of vaccine and treatment to cure Covid-19, it is suggested that a data-driven reflection needs to be carried out. Proposed research makes the use of Machine Learning to fulfill the same for accelerated recovery. In the process, it looks forward to identifying significant correlations that are associated with Coronavirus. The research includes both supervised learning & unsupervised learning for greater accuracy.

Supervised Machine Learning identifies 'field Importance' and 'partial dependence' to identify correlations across variables at the same time, unsupervised Machine Learning enlightens 'associations' as well as 'component weightage' using the curated data. Using predictive analytics given study evaluates several permutations and combinations to offer recommendations. Such interaction and integration with near-time dataset using the Machine Learning may yield an effective containment of Coronavirus outbursts. In the current state of Covid-19, the data-driven prediction will help the society to find means to survive during the pandemic, while it lasts.

Research Objective

Research Gap

Bluhm et al. (2020) believe that the ongoing pandemic may last considerably longer, and there may be a second wave of infection. Presuming the vaccine and its mass administration is still out of reach, existing measures of social distancing do not appear to be sustainable.

As established earlier, emerging economies may suffer substantial losses by the time clinical trials develop control over the pandemic. This fact brings us to the development of parallel strategies to deal with Covid-19.

Arguably the least explored area of Artificial Intelligence in healthcare is its role in governance, and researchers have also observed the limited impact A.I. has had in the management of Covid-19 (Ashrafian & Darzi, 2018; Hu et al., 2020). It reflects the need for translating insights from Machine Learning models to Covid-19 affected environments.

Research Questions

In consideration of insights retrieved via Machine Learning, it is possible to open the global economies and establish the normalcy in economic activities.

To achieve the same, the strategic review of Covid-19 related factors needs to be made by governing authorities.

Hence proposed research aims -

- To extract a data-driven solution to contain the current virus outbreak
    - That is sustainable in emerging economies
    - That can be applied to communities
- To identify strategies to avoid the future virus outbreak
    - That exist without strict social distancing norms
    - That manages the coronavirus outbreak at a macro level

Research Methodology

Data Collection

The research followed the 'quantitative research' methodology to be able to draw insights from curated datasets. A total of 170 countries was selected as a sample based on the gravity of impact experienced during the Covid-19 event. The sample size represented Africa, Asia & Pacific, Europe, Oceania, Middle Eastern, and the Arab States as well as Southern & Northern American regions to achieve accurate representation. The identification of direct and indirect measures was made through a comprehensive review of the literature. In line with the assessment of the literature, eleven measures were identified for data collection.

The range of the collected dataset included the very first reported instance of Coronavirus until July 2020. Further scientific evidence was compiled from various sources and consolidated for predictive modeling. The

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dataset related to food consumption patterns was collected from Helgi Library (2020), and global vaccination policies were retrieved from BCG World Atlas (2020) to identify relevant associations.

Data Modelling

The data staging was done with the Covid-19' Recovery Index' as the target value. Lower target value represented better outcomes (or improved recovery rate) arising from the pandemic. As per Ooms & Spruit (2020), there have been many instances where data science has leveraged the use of Machine Learning techniques in the healthcare sector, and considering the same, a set of models were created and evaluated to generate Covid-19 related predictions. Machine Learning offered the ability to program real-world problems, explicitly using computer algorithms and statistical techniques. To accomplish the research outcome, a Machine Learning model was trained to identify the probable effect of Covid-19.

In general, Machine Learning is categorized in supervised (i.e., consists of output variables that are predicted from input variables) or unsupervised (i.e., deals with clustering of different groups for an intervention) learning process that simulates complex real-life scenarios. (Battineni et al., 2020) In the given study, supervised Machine Learning was achieved using Ensemble Modelling, while unsupervised learning was carried using Associations Modelling. The default ML model was built using Decision Tree (DT) algorithms, where the datasets were configured for identifying the 'Recovery Index' of Covid-19 as the predictive outcome. During model building, a supervised Machine Learning algorithm required a dataset that is split into a 'training' data set and a 'test' or 'validation' data set. A Machine Learning model was then trained using 80% of the data to predict a Recovery Index accurately. As the number of measures reflected on the Covid-19 Recovery Index, the accuracy of predicting the same improved significantly over the period. Post model training, the 'trained' Machine Learning model was validated – post evaluation of its predictive performance. The evaluation was performed using 20% of the test data.

The performance of the algorithm was tested by splitting the initial data through the random sampling, into training and testing sets being mutually exclusive subsets. This event enabled validation of the Recovery Index in predicted versus actual scenarios to meet a predetermined threshold for model evaluations. This process reflected positively on both the reliability and validity of the model. The 'validated' Machine Learning model was then applied to a new dataset for gauging target value. Model deployment supported the identification of factors and observed significant correlations that predicted the Covid-19 Recovery Index. This approach of model deployment to predict the Covid-19 Recovery Index was a key component of technology management that generated recommendations for accelerated recovery.

Data Analysis

Machine Learning Model

According to Caballé et al. (2020) in Artificial Intelligence, Machine Learning stands out as a method for providing tools for intelligent data analysis. There are specific algorithms that are used to develop models with predictive capabilities, and the selection of such algorithms depends on the research objective. The algorithm learns from the existing data, can be used to build complex models and predicts the target values (Arpitha et al., 2018). However, as per Feldman et al. (2017), the ability to derive informative insights requires more than the processing and execution of Machine Learning models. Rather, it calls for a deeper understanding of the data on which the models are executed.

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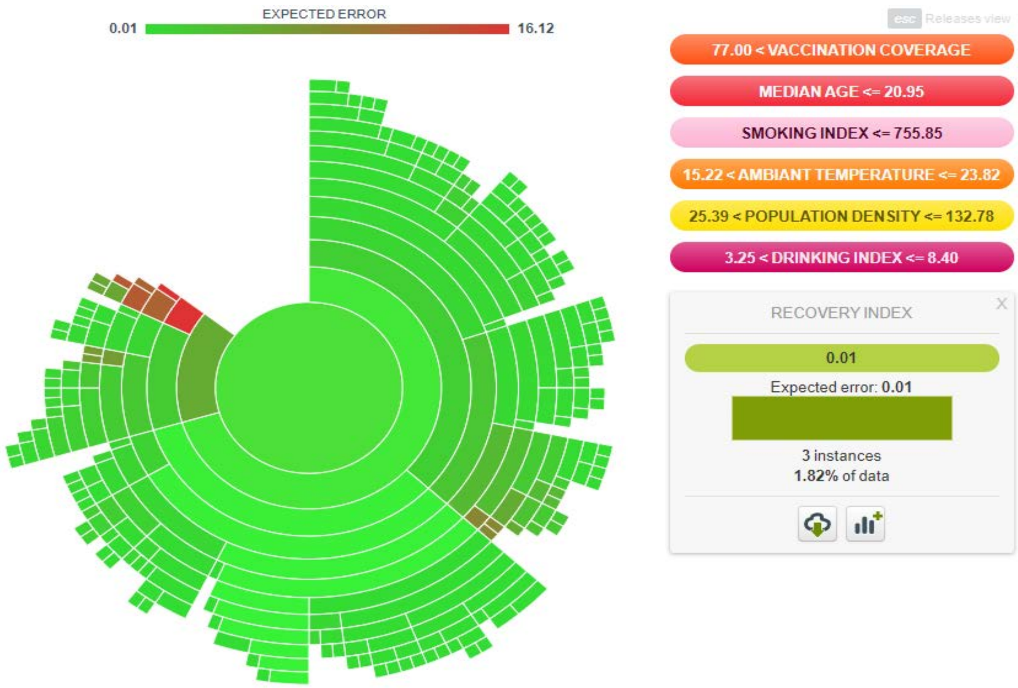

Figure 1 - Sunburst analytics chart of an instance for Covid-19 recovery

For the current study, a dataset was created with relevant fields where both supervised and unsupervised learning modes were carried out for the development of multiple models. The default model utilized Decision Trees (DT), and one of its instances as Sunburst analytics chart is as shown in Figure 1.

A Machine Learning model was trained with an algorithm that can be used to reason over and learn from previous outcomes to recognize patterns. The areas in green color represent the accuracy level of the 'Sunburst chart,' as shown in Figure 1. The accuracy is derived from associated factors predicting the Recovery Index using Decisions Trees. As can be seen from Figure 1, Machine Learning algorithms require the fitting of data to statistical models. Unlike traditional model fitting, the goal of a Machine Learning algorithm is to make accurate predictions using the input data. According to Talevi et al. (2020), the parameter values returned by the model are generally of secondary interest; however, to interprets parameter values in a meaningful way, another set of supervised learning (Ensemble modeling) and unsupervised learning (Associations modeling) was carried out during the presented research.

Ensemble Modelling

Ensemble learning is commonly applied to Machine Learning models to improve efficiency and reduce the risk in the decision-making process. In this approach, predictions from a diverse set of models are combined to yield the best fitting model (Battineni et al., 2020). In supervised learning, aggregated predictions from an ensemble model of diverse classifiers consistently outperform individual methods (Ahsen et al., 2019). However, the difficulty of the optimization problem during data fitting depends on the nature and complexity of the real-world situation, and also the determination of metrics (that are an optimal fit for precise decision making) remains a challenging task (Chui et al., 2017; Tan et al., 2020).

There were several factors being considered while building the Ensemble model. However, the Median Age showed the greatest importance (33.58 %), as per Figure 2.

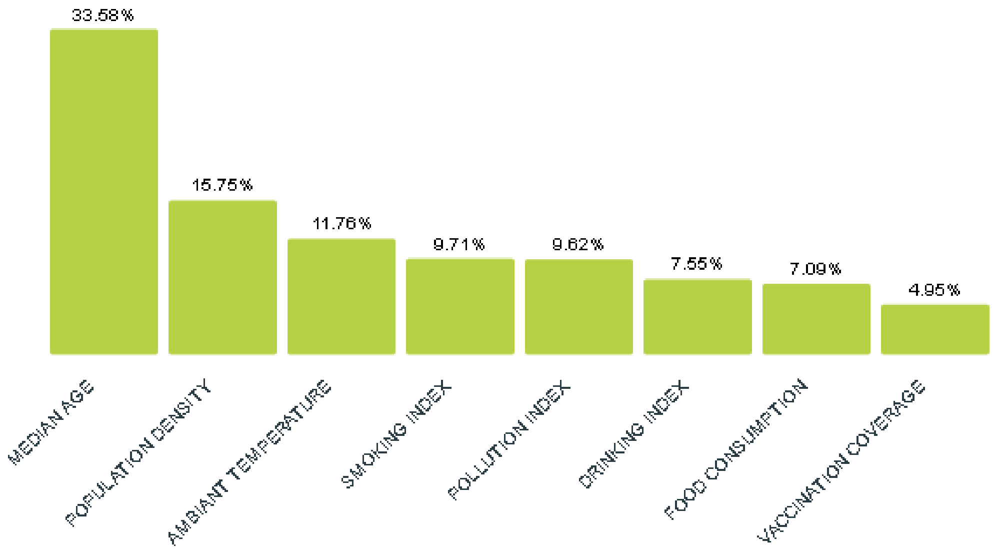

Figure 2 - Fields of Importance affecting Covid-19 recovery

Figure 2 signifies the importance of Ambient Temperature on the exponential growth rate of Covid-19 infection. (Livadiotis, 2020) Interestingly, Smoking Index has also shown considerable importance. In line with research conducted by Hayden & Parkin (2020), countries with a higher smoking index have observed an unsatisfactory Covid-19 recovery rate. The impact of the food consumption pattern can also be seen above in Figure 2. As food consumption includes uses of 'edible spices' as corroborated by Boukhatem & Setzer (2020), it would seem reasonable to assume that these products contain antiviral compounds. Figure 2 also shows the importance of population density that suggests the necessity of avoiding situations in highly populated areas to limit the spread of Covid-19. A similar observation was made by Rocklöv & Sjödin (2020); however, such observation may not always be universally accurate and warrants further investigation when using Machine Learning.

Although it may appear that some factors have low relevance to Covid-19, the complexity of the study involves finding that indirect associations that can be achieved using a separate Machine Learning model. Hence to re-confirm the output of the Machine Learning model, associations were identified through an unsupervised modeling technique called 'Associations modeling.'

Associations Modelling

Associations modeling is an unsupervised Machine Learning technique that explores unique relationships among variables in a large dataset. Unlike conventional modeling techniques, associations algorithms measure degrees of similarity to identify hidden correlations to generate an exploratory graph, as displayed in Figure 3.

Associations are the product of the intersection between the antecedent variable and the consequent variable. The association is determined using the number of instances, probability, confidence level, and occurrence in the intersected dataset. The values of an association and leverage can be set by researchers to reduce the complexity of analysis.

The associations (K=5) and leverage (6.18%) based on curated data have been represented using Figure 3.

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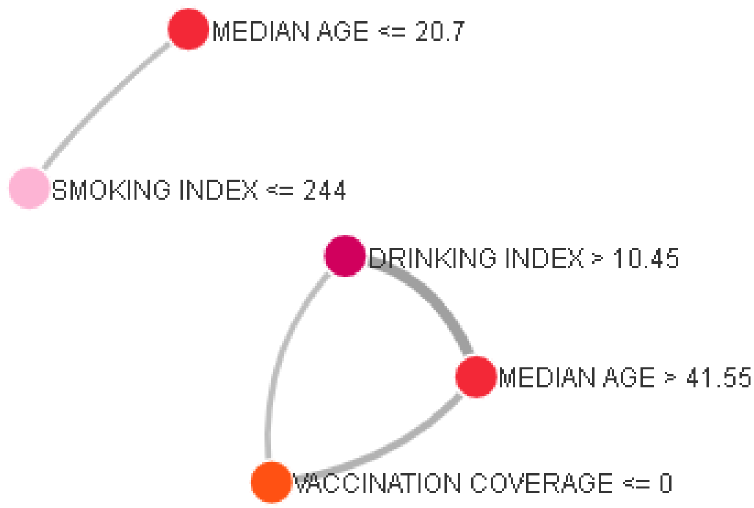

Figure 3 - Significant associations derived from the dataset

As per the model displayed in Figure 3, there exists a clear association between Median Age with Drinking Index as well as with Vaccination Coverage. The model shows that people of median age (>41.55), with no BCG vaccination, shall avoid consuming alcohol after a specific limit (Index 10.2) as it may negatively affect the Covid-19 recovery rate. Another study by Urashima et al. (2020) presented a similar hypothesis where BCG vaccination appears to be associated with reduced mortality of Covid-19.

The presented model further implies that populations with a specific age group (20.7<) may get adversely affected in case the Smoking Index exceeds 244. Although this is an association based analysis, it does elaborate on the impact of smoking on the recovery rate of Coronavirus infected persons (Berlin et al., 2020; Reddy et al., 2020; Saadat et al., 2020). The act of smoking has several consequences as active smoking affects not only an individual but also affects people that are around. Further, in a social setting, smoking may also lead to minimal social distancing, which inevitably reflects on the Covid-19 Recovery Index.

Reliability

The current adoption of Machine Learning technology in healthcare emphasizes the need for characterizing model reliability. Considering the purpose as well as the application of Machine Learning in healthcare, it is imperative to conduct a thorough verification to support robust decision making (Rodr et al., 2006).

Reliability is a measure of consistency, and it focuses on the re-production of results when research is repeated under the same set of conditions. The reliability of the ML training process in the current study was achieved during model training automation process using the following steps -

1. Automated data extraction
2. Feature extraction
3. Model training and testing
4. Model selection and
5. Model evaluation

Reliability was further tested by checking the consistency of results across parts of the test itself. The approach involved the creation of ML models and the comparative analysis of the performances between the test set and a training set of data. The data reliability was identified upon training the dataset (using 80% data) and testing the model with the remaining training dataset (using 20% data).

To avoid the inefficient models in Machine Learning, quality checks were conducted on the following aspects:

- ✓ Data Quality
- ✓ Features Importance
- ✓ Model Matrices

Thus, as recommended by Cabitza et al. (2019), the presented study minimized the uncertainty of the Machine Learning model.

Validity

Validity is about the accuracy of a measure that confirms the extent to which the results measure; what they are supposed to measure. Model validation is performed to assess the model's predictive performance using a dataset that was not a part of the original build of the model.

As suggested by Huber-Carol et al. (2008), in the given study, validity was achieved by checking how well the results correspond to Goodness-Of-Fit. The Goodness-Of-Fit indicators summarize the disparity between observed values and the model's anticipated values. As far as a Machine Learning algorithm is concerned, a good fit is when both the training data error and the test data are minimal. The same is evident in the presented research based on the following characteristics -

A) MEAN ABSOLUTE ERROR - 0.11

Statistically, Mean Absolute Error refers to the results of measuring the difference between two continuous variables. It is the average of the absolute values of the differences between the target predicted by the model and the true target.

B) R-SQUARED VALUE - 0.95

R-squared is a statistical measurement of the vicinity of the data -points to the fitted regression line. It is also called the coefficient of determination for multiple regression. It is a measure of how a model performs than predicting the mean of the test set.

The Goodness-Of-Fit of a Machine Learning model explains how well it matches a set of observations and based on the ML Model output (from Table 1) following facts were validated –

More Significant Factors:

- AMBIENT TEMPERATURE, VACCINATION COVERAGE, MEDIAN AGE, SMOKING INDEX

Less Significant Factors:

- POPULATION DENSITY, POLLUTION INDEX, DIET CONSUMPTION, DRINKING INDEX

In accordance with existing literature, similar observations were reflected in the 'Discussion' sections.

Data-driven characteristics represent the level of 'Significance' as well as 'Confidence' of factors as mentioned below -

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Table 1 - Significant factors and Confidence levels of test data

CONFIDENCE	POPULATION DENSITY	POLLUTION INDEX	AMBIENT TEMPERATURE	VACCINATION COVERAGE	MEDIAN AGE	DIET CONSUMPTION	SMOKING INDEX	DRINKING INDEX
3.31861	0	0	**0.00209**	**0.71612**	**0.12009**	0	**0.16171**	0
0.15803	0	0.00152	0.00175	0.71013	6.80E-04	0	0.28365	0.00228
6.21581	0	0	0	0	**0.991**	0	0	**0.009**
1.5993	0	0	0	0	0	0	0	0
0.47409	0	0	0.00664	0.74639	0.24648	0	4.90E-04	0
8.11216	0	0	0	**0.95251**	**0.04749**	0	0	0
0.77364	**0.23137**	0	**0.01746**	**0.74232**	0	**0.00384**	**0.005**	0
0.10535	0.23008	0	0.01737	0.74013	0.00362	0.00382	0.00498	0
0.79015	**0.02908**	0	**0.02152**	0	**0.90103**	0	**0.04019**	**0.00818**
0.10258	0	0	0	0.74986	0.24482	0	0.00531	0
0.05268	0.23058	0	0.0174	0.73818	0	0.00886	0.00498	0
0.33955	0	0	0.00175	0.71078	0	0	0.28389	0.00358
6.21581	0	0	0	0	**0.991**	0	0	**0.009**
0.26338	0	0	2.10E-04	0.75006	0.24442	0	0.00531	0
1.5993	0	0	0	0	0	0	0	0
0.05268	0	0	7.70E-04	0.74927	0.24463	0	0.00533	0
0.42141	0	0	0	0.74809	0.23872	0	0.01319	0
0.36873	0.03749	0	0.00977	0	0.89934	0.00512	0.04012	0.00817
0.36873	0.2302	0	0.01738	0.73858	0	0.00887	0.00498	0
0.50055	0	0	2.10E-04	0.7497	0.24477	0	0.00531	0
0.53061	0.23053	0	0.0174	0.73963	0.00362	0.00383	0.00499	0
0.03841	3.00E-05	0	7.40E-04	0.74928	0.24463	0	0.00531	0
0.15803	0.23001	0	0.01736	0.73798	0.00383	0	0.01082	0
1.5993	0	0	0	0	0	0	0	0
0.02934	0.23056	0	0.0175	0.73818	0.00294	0	0.01082	0
0.93905	0	0	0	**1**	0	0	0	0
0.15803	0	0.00152	0.00175	0.71013	6.80E-04	0	0.28365	0.00228
0.36873	0.03749	0	0.00977	0	0.89934	0.00512	0.04012	0.00817
0.47409	0	0	0.00175	0.71077	0.00133	0	0.28388	0.00228
0.31606	0	0.0012	0.00175	0.71037	6.80E-04	0	0.28372	0.00228
0.01174	5.00E-05	0	7.40E-04	0.74927	0.24463	0	0.00531	0
11.4336	0	0	0	0	**1**	0	0	0
0.02075	0.23056	0	0.01739	0.73817	0.00302	0	0.01087	0
0.08337	0.23058	0	0.01739	0.73826	0.00295	0	0.01082	0

Table 1 infers from the 20% of test data (output from ML Model, including 34 countries) that four factors have high significance as well as confidence than other factors included in the Covid-19 dataset.

Evaluation

Decision Tree

Reliability and validity have been established in given research to evaluate the quality of the proposed research. It indicates how effectively the current built of the Machine Learning model can make predictions. There are several ways to use data and reflect the trends and make predictions. Each one uses a technique that can be applied to infer from output structure (Supervised Learning) or represents specific data clusters (unsupervised

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learning). The default model for given research is based on Decision Trees (DT) that are predictive representations of datasets. Decision trees are a hierarchical way of partitioning the space, where the goal is to develop a model that predicts the value of a target variable based on several input variables (Caballé et al., 2020).

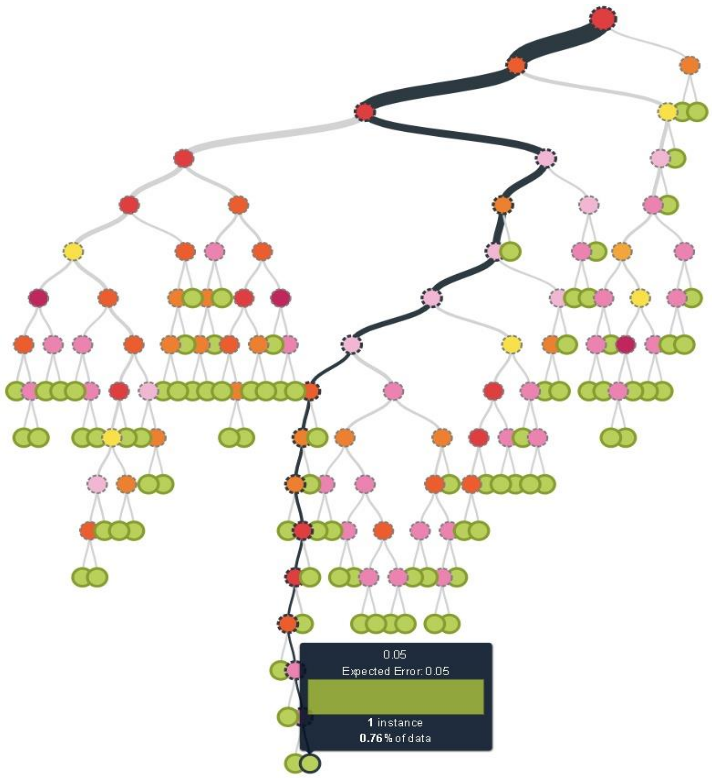

Figure 4 - Decision Trees Model developed for Covid-19 Recovery Index

As shown in Figure 4, the Decision Tree evaluated multiple fields from the given dataset and achieved Recovery Indices based on the field of importance. A Decision Tree learns by splitting the source dataset into subsets that are based on an attribute value test. When a DT is used for classification activities, it is more appropriately referred to as a classification tree. On the other hand, it is called a regression tree when used for the regression tasks. Such a model is expected to make sufficiently accurate predictions for the intended use, which in this case, is the Covid-19 Recovery Index.

As Figure 4 displayed a regression tree with a complexity, Principal Component Analysis (PCA) was conducted to be able to maintain accuracy during predictions.

Principal Component Analysis

Principal Component Analysis (PCA) is a statistical technique that is used for dimensionality reduction to improve model performance. Because of unsupervised learning, PCA seeks to cluster the data without prior training. During the presented study, the dataset was evaluated using Principal Component Analysis to overcome feature redundancy. It also reduced the complexity of the model and provided greater computation efficiency.

Figure 5 below shows the Scree plot of Principal Component Analysis with variances -

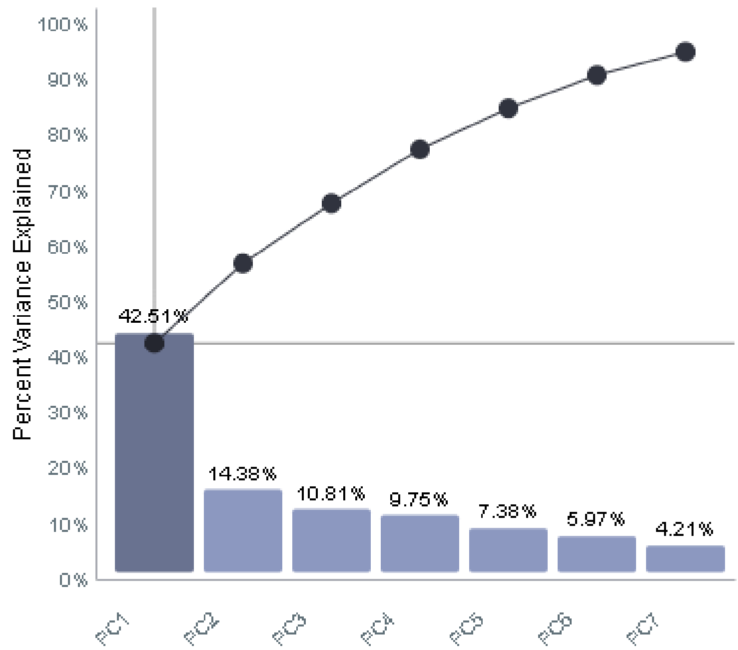

Figure 5 - SCREE plot showing PCA variances

A Scree Plot is a graphical utility used in the selection of the number of factors to be considered in a Principal Components' Analysis (or factor analysis.) Conceptually, the Scree Plot supports visualizing the magnitude of the variability associated with every component extracted through Principal Component Analysis (PCA).

In the given study, the Scree plot facilitated the examination of the pattern of decreasing variability attributable to each successive component that may be used for component selection and feature extraction.

As Figure 5 re-confirms, the selected Principal Components (Set 1) used in current research possess the highest variance. It translates into the fact that model selection by the researchers was robust. Also, the variables identified for the study were unique and statistically independent.

Discussion

Observations

Machine Learning, a subfield of Artificial Intelligence, leverages numerical techniques derived from computer science, mathematics, and statistics to automatically 'learn' by processing massive datasets. Machine Learning can provide several indispensable tools for intelligent data analysis. According to Ashrafian & Darzi (2018), Machine Learning has the potential to address complex real-world problems, and for current research, it played a significant role by supporting predictive modeling.

Predictive models in Machine Learning can effectively support decision-making activities (Battineni et al., 2020).

Additionally, Caballé et al. (2020) believe that technology is currently well suited for analyzing medical data and presents a wide range of possible applications. Unlike early A.I. systems, where it relied heavily on expert-derived rules to perform analytical processing; Machine Learning can fulfill tasks such as sensing, learning, reasoning, to make predictions and support serendipitous discovery (Morande & Pietronudo, 2020).

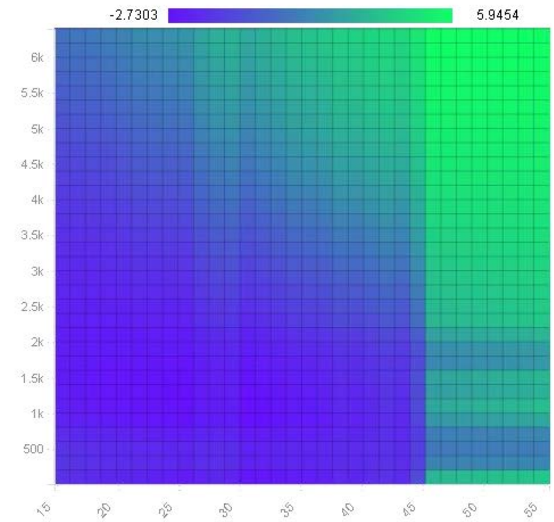

Figure 6 - PDP against Smoking Index (X-axis) & Median Age (Y-axis)

One of the outputs of Machine Learning models is in the form of Partial Dependence Plots (PDP). Partial Dependence Plots show the dependence between the target response and a set of target features, marginalizing over the values of complement features. As it can be observed from Figure 6, Partial Dependence Plots with two target features show the interactions among the two features (Molnar, 2019). Using the same, researchers can interpret the relationship between the expected target response as a function of the target features.

Using PDP, it is possible to predict and analyze the impact of different factors on the Covid-19 Recovery Index. In line with the inference drawn by Wyper et al. (2020), Figure 6 displays population vulnerability to Covid-19 concerning the Median Age. It also signifies one of the factors (Smoking Index) affecting the recovery of the patient. Partial Dependence Plots further presents a greater depth of insights, as described in the next section.

Insights

The use of real-life data identified important correlations, discovered unseen trends and suggested best practices regarding Covid-19. Following are the salient points with respect to various factors -

[A] Median Age

The age of an individual appears to be the most significant factor during the Covid-19 Pandemic (Karadag, 2020).

The Machine Learning model displayed that individuals above the age of forty-five fall under the 'High Risk' category. Other studies carried out by Solomou & Constantinidou (2020) also affirmed that age plays an important role when dealing with the Covid-19 pandemic.

[B] Smoking Index

Although the current study by Cai (2020) does not support smoking as a predisposing factor for Covid-19 infection, the data-driven approach tells a different story. It suggests that Smoking Index is one of the significant factors in the Covid-19 pandemic.

The Machine Learning model shows a significant correlation between Age and Smoking Index as well. It further suggests that smoking deteriorates Recovery Index and adversely affects an individual beyond the age of 25.

Covid-19 being a respiratory condition, supporting argument can be made, stating smoking increases the risk of viral infection (Berlin et al., 2020).

[C] Vaccination Coverage

Gursel & Gursel (2020) have hypothesized that a limited number of Covid-19 cases in Asia and Africa might reflect from the 'BCG immunization induced heterologous protective activity' of the vaccine.

According to the Machine Learning model, after the age of 45, if not vaccinated - an individual can experience a weaker Recovery Index. This observation further aligns with the claim made by Iwasaki & Grubaugh (2020), where the BCG vaccine may induce certain immune stimuli to gain resistance against pathogens. That said, the ML model showed a positive but limited impact of BCG vaccination on the recovery rate, which may not be very conclusive and may call for additional data required for future studies.

[D] Ambient Temperature

The Machine Learning model displayed that temperature range from 7-15 °C (degree Celsius) presents the lower Recovery Index, and the age group beyond the age of twenty-seven might get exposed to the adverse effect of Covid-19 in cold regions.

Research conducted by scientists on similar grounds affirms the impact of temperature on the number of Covid-19 patients (Bukhari et al., 2020; Jiang et al., 2020).

[F] Drinking Index

The Machine Learning model also inferred that after the age of forty, the Recovery Index suffers if the Drinking Index exceeds 3.0. That re-confirms, drinking alcohol does have some impact on the Covid-19 Recovery Index.

Szabo & Saha (2015) also believe that exposure to alcohol may harm host response and may impair immune function that can enhance susceptibility to viral infection. Although Drinking Index is one of the factors identified in the given study, the significance is relatively low, as shown in Table 1.

[H] Food Habits

The data modeling suggests that the inclusion of spices in the diet does positively affect the Covid-19 Recovery Index. This may also translate into a flat Covid-19 mortality rate observed in Asian and African regions based on respective diet patterns (Debnath et al., 2020).

As per Boukhatem & Setzer (2020), it would be reasonable to assume that herbs or spices that contain antiviral compounds can provide health benefits against viral infections.

[E] Population Index

Ahmed et al. (2020) suggest that population density plays an essential role in the spreading of Covid-19 & higher population density poses an extreme risk.

Surprisingly, the ML model shows that the Recovery Index improves as population density becomes higher.

This observation is inclined towards 'herd immunity,' which may not be a practical approach as far as Covid-19 is concerned. (Iwasaki & Grubaugh, 2020) It may also be an indirect effect observed by the administration of the BCG vaccine that is more common in countries with higher population density (Zwerling et al., 2011).

Such circumstances call for additional studies for the reasoning of factors in question.

[E] Pollution Level

One of the preliminary studies by Han et al. (2020) suggests that Pollution Levels are associated with Covid-19 infection. However, according to the Machine Learning model, the Pollution and Recovery Index are not highly correlated.

(In the future studies using A.I. driven fusion modeling may reflect some co-relation but is unlikely to be highly significant.)

It must be noted that the above interpretation drawn from Machine Learning modeling applies only to the macro level. This is because collected data is based on population-level, and hence insight derived for the dataset can only be transferred to masses.

Implications

Over the last few years, the immense increase in computational power and data storage has enabled A.I. (more specifically, Machine Learning) to provide almost unbelievable classification and prediction performances compared to well-trained humans (Clifford, 2020). According to Stiglic et al. (2020), emerging Machine Learning algorithms are beginning to transform the healthcare sector, where it is possible to classify interpretability approaches into two types. The first type focuses on personalized interpretation (local interpretability) while the second summarizes prediction models on a population level (global interpretability).

With a focus on the developing world, the research presents a data-driven but non-clinical approach that assumes the time barrier for the availability of Covid-19 treatment. The study attempts to provide insights that can be adopted during policy-making exercise on a population level for effective governance. Research provides a set of practical aspects related to Covid-19, including causal effect leading to the prediction of health-related outcomes. The same can be applied to the communities for a healthier society.

Limitations and Future possibilities

Every Machine Learning experiment begins with data curation required to build a model, and a model will be only as good as the data from which it is derived. Therefore, data quality is often highly dependent on data aggregators. As data curation and preparation are a cornerstone to develop a reliable model, the results presented in this study are dependent on the collected dataset. While a significant effort has been undertaken for accurate data modeling, the overfitting of data in the Machine Learning may bring in less clarity in the output. Such conditions may make it challenging to identify associations in the dataset that are not genuinely intrinsic to the predictions made. Furthermore, drawing on data from an increasingly diverse set of sources, it presents an incredibly complex set of attributes that must be accounted for throughout the Machine Learning modeling (Feldman et al., 2017).

It must also be noted that the Machine Learning outcomes are derived from data available until July 2020. Any mutation of the Covid-19 virus may differ from current observation and reduce the value presented by the existing set of data. As per the suggestions by Urashima et al. (2020), the observation made in the study needs to be further examined and proved by randomized clinical trials. The predictive inferences in the given research are broad in nature and do reflect on the macro level only, and to make these insights applicable to micro-level data needs further augmentation.

In the near future, researchers plan to engage in personalized interpretation using a longitudinal approach. Beyond that, future research would segregate and reflect on the data by classifying it as per the regions to provide detailed insights.

Conclusion

The Covid-19 pandemic has changed the people's lifestyle, caused extensive losses, and threatened the sustenance of millions of people. Overall, the economic activities have been suspended, and commercial activities have been hibernated to control the spread of the virus.

As advancements in healthcare fields are expanding the access to electronic data, the utilized approach emphasizes on accelerated Covid-19 recovery through technology management. Using substantial computation power, the healthcare field can apply Artificial Intelligence to address challenges in healthcare, especially during a current pandemic. Although many of these Machine Learning systems remain experimental, it ultimately presents the most substantial transformative role in healthcare governance. With the proposed research, Machine Learning modeling has evaluated multiple scenarios to focus on the Covid-19 Recovery Index. The research presents a strong case where Machine Learning models can be used to identify specific traits and rescue masses from the impending outcome of Covid-19.

As the given study feeds on near-time data and comprehensive academic underpinning, the generalization of developed Machine Learning models is possible. The insights derived from this research are applicable to regional and national levels and can be used by both developed and developing countries to develop strategies. Like other revolutionary technologies, Machine Learning should consider the limitations on algorithm development and understanding its appropriateness to apply.

While researchers are progressively attracted by predictive modeling techniques, Machine Learning is likely to play a vital role in the advancement of healthcare and enhancement of societal health. The data-driven insights from the presented research could offer advice to accelerate the Covid-19 recovery and make policy recommendations to help administrators develop well-informed health policies.

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Research Article

Does Structural Power Matter? Board Attributes and Firm Performance: Moderated by CEO Duality

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Purpose- The study investigates the moderating role of Chief Executive Officer Duality onboard attributes and firm performance of companies listed in Kenya.

Design/Methodology- The research used a longitudinal research design. Panel data were derived from published accounts for sixteen years that is from 2002-2017. IGLS regression models were used to test the hypothesis.

Findings- The empirical results indicated that the independence of the board, the size of the board, and the duration in which the board member served the organization positively influence the firm performance. However, CEO duality does not moderate the relationship.

Practical Implications- Regulatory bodies such as NSE and CMA in Kenya should ensure that listed firms have more independent directors serving a board, ensure a reasonable size of the board and increase the board tenure to enhance firm performance. Further, the combined roles of the CEO and chairman may not influence the efficiency of the board in the Kenyan context.

Introduction

Firm performance encompasses the ability of an organization to maximize the shareholders' wealth and thus increase the firm value (Sarhan, Ntim, & Al-Najjar, 2019). However, in recent years financial crises, economic collapse, and fall of large corporations have resulted in investors of the firms to endure severe losses (Martín & Herrero, 2018). Hence, this has brought corporate governance to the limelight, especially about the board's function in safeguarding the owners of capital wealth.

Agency theory emphasizes having on board directors who can monitor and control the management, discipline the managers and ratify and approve significant decisions that enhance the increase in the value of the firm (Katti & Raithatha, 2018). However, board ineffectiveness has mostly been associated with the structural power that a CEO has been conferred (Boyd, 1995; Duru, Iyengar, & Zampelli, 2016; Harjoto, Laksmana, & Lee, 2015; Ntim, 2016). As such, the subject of CEO duality has been a matter of contention in accounting and finance literature.

Although previous studies have extensively researched on board attributes and firm performance, the results are inconclusive. While studies have shown positive relationships between board attributes and firm performance (Han, Nanda, & Silveri, 2016; Sarhan et al., 2019), others have shown negative relationships (Boyd, 1995; Duru et al., 2016; Garkaz, Abdollahi, Niknam, & Branch, 2016; Martín & Herrero, 2018). Whereas, there are studies which have not shown significant relationships (Sheikh, Shah, & Akbar, 2018). The reason that can explain the variability of the results is the legal and institutional settings, which is quite different in developed and emerging countries such as Kenya. Hence the need to conduct the study in Kenya.

In addition to the mixed results, although prior research has expanded more on different board attributes and firm performance, little is known about the influence of the CEO power on the effectiveness of the board toward enhancing performance. Studies have shown that CEOs can have powers over the company's functions and effectiveness since the approval of most decisions depends on them. Other studies have further shown that Chief Executive Officers can also influence how directors are appointed, thus compromising independence and board functioning. Thus, this research furthers extant literature by investigating the moderating role of Chief Executive Officer structural power as determined by CEO duality on the relationship between board attributes and firm performance in Kenya.

Theory and Hypotheses Development

This research was anchored on both agency theory and stewardship theory. While agency theory views executive managers as opportunists and thus the need for the shareholders to appoint the board to monitor and control such managerial opportunistic activities, stewardship theory views managers as custodians and stewards who are motivated to serve the same interest as the owners of capital. Agency theory assumes that the agents understand more about the company than the owners; hence they can decide to serve their interest if proper monitoring and control are not put in place. It, therefore, advocates that a thin layer in the form of a board should be introduced to curtail such opportunistic behaviors. Previous research has established that boards are instrumental in the decision making process.

Nonetheless, there is a debate in prior literature on identifying the optimal attributes that the firm should have to ensure efficiency. Further, CEOs form part of the board and are in charge of the day to day running of the business. In circumstances where firms practice duality, CEOs may have unvetted powers. The repercussion of these powers has been explained in different versions by the agency theory and stewardship theory. Agency theory posits that introducing the board of directors will aid in monitoring managerial activities and approving decisions of the management and hiring and firing senior management, especially the Chief Executive Officer. Unfortunately, some studies reveal that the CEOs have more powers and thus affect the effectiveness of the

board. In that case, they ensure that they create a friendly board that cannot question their work. Stewardship theory, on the other hand, assumes that Chief Executive Officer understands his/her duties and works towards achieving the shareholder's goals, thus need not be monitored. Therefore, the study sought to understand whether CEOs in Kenya context, with duality powers, work as agents as posited by the agency theory or work better as stewards as explained by stewardship theory.

Board Attributes and Firm Performance

The board of directors acts as monitoring mechanisms that reduce the scrimmage between the owners of capital and the managers. The more power the board holds, the less likely the probability of opportunistic behaviors by the managers. Put simply, when the monitoring by the board is not adequate, it augments the ability of the agents to dissipate the shareholders' resources (Al-Matari, Al-Swidi, & Faudziah, 2014; Naseem, Xiaoming, Riaz, & Rehman, 2017; Sadeghi Panah & Boroumand, 2015). The board of directors' oversight ability roles becomes straightforward and easy to implement by splitting the CEO and chairman role independently. The independency dilutes the CEO`s power and increases the board of directors' effectiveness to perform their oversight role. To enhance independence, some of the internal mechanisms employed are the concern of increasing representation of outside independent non-executive directors and having a large board. Large boards are hard to be controlled by the CEO contrary to small boards but interfere with group dynamics (Jensen, 1993). Thus, the board attributes in this study refer to the size of the board, board independence, and board tenure.

Board independence and firm performance

Independent directors refer to directors who are not affiliated with the organization in any manner. Independent directors have been viewed by literature as more efficient in increasing the firms' value (Smulowitz, Becerra, & Mayo, 2019). This has been associated with the vast expertise they gather from holding multiple boards. The other set of literature argues that independent directors have less information and may not be conversant with the company's operations, thus may not be reliable in increasing the firms' value. Further, there is an ongoing debate in the literature on board independence and its impact on firm value. Several scholars reckon that independent directors are not independent in their decision makings. Instead, they act according to the interest of the sizeable net-worth shareholder that holds a significant say in the performance of the company. Notwithstanding that, independent directors control the activities of the firm at all levels and even hold power to appoint and dismiss top-level managers in the best interest of the organization at any point in time (Naseem et al., 2017).

Earlier studies have shown varied results about the relationship between the board of directors' independence and the performance of a firm. One stream of literature has shown that there exists a positive relationship between board independence and firm performance (Han et al., 2016; Sarhan et al., 2019). The other stream has established a negative association between board independence and firm performance (Duru et al., 2016; Martín & Herrero, 2018). Contrary to these results, Pervin and Rashid (2019) did not establish any significant relationship between the independence of the board and firm performance. Thus, advancing from the inconclusive results, we hypothesize that;

Ho1: There exists a positive and significant relationship between board independence and firm performance

Board size and firm performance

Board size refers to the number of directors serving the given organization (Hoppmann, Naegele, & Girod, 2019). While agency theory advocates for smaller boards that allows easy coordination and minimum cost, resource dependency theory argues that long-tenured boards are more versed as they incorporate more expertise in different disciplines and a further increase of independent board members (Kalsie & Shrivastav, 2016).

Specifically, the corporate governance guidelines issued in 2002 by Capital Market Authorities in Kenya requires that all listed firms should have board members of sufficient size. The word "sufficient size" does not give the exact required number of board members, but instead, it leaves it open for companies to incorporate members whom they feel is sufficient to serve the board. Thus, it is clear that the sizes of the boards will vary across the firms depending on the size of the firms and the nature of the business.

Scholars in finance have shown mixed results on the relationships between the size of the board and firm performance. A stream of literature has echoed that large boards increase firms' value due to collaborative expertise that is acquired from experienced board members, the inability of the CEO to manipulate large boards due to different personalities, and the fact that it increases the possibility of inclusion of more independent board members (Merendino & Sarens, 2020). Other studies have argued that smaller boards are more efficient in increasing firm value in that it reduces costs and dormant members, enhances easy coordination, and provides board cohesion (Kao, Hodgkinson, & Jaafar, 2019). Hence it is not clear from the literature whether firms should go for smaller boards or large boards. Thus, advancing from the inconclusive results, we hypothesize that;

Ho2: There exists a positive and significant relationship between board size and firm performance.

Board Tenure and Firm Performance

Tenure of the board refers to the duration in which board members have served the board. When board members are allowed to serve for a more extended period, they tend to understand the operations of the company more and thus become more productive in decisions they make of the company, considering that they understand the industry better. Other sets of literature argue that when board members are allowed to serve for a more extended period, independency is compromised (Neville, Byron, Post, & Ward, 2019). Thus, they argue that shorter serving directors are better since it allows rotation of directors allowing those with low performance to be replaced by more productive and efficient directors. Further, the literature argues that it allows the distribution of expertise and knowledge gathered from serving other boards(Neville et al., 2019).

Scholars have shown contradictory results on the association between board tenure and firm performance. In two studies, the results yielded a positive relationship (Sarhan et al., 2019; Sheikh et al., 2018). These studies argued that long-tenured boards are more informed and understand the firm's systems hence cannot be controlled by the management. Other studies have yielded negative relationships (Al-Matari et al., 2014; Boyd, 1995). These studies have further echoed that board tenure acts as a proxy of board independence, and thus the longer the period a board member serves, the lower the board's independence.

Interestingly, others have shown no significant relationships between board tenure and firm performance (Saleh, Latif, Bakar, & Maigoshi, 2020). Hence from the literature, it is unclear how a director should serve and remain productive to enhance firm value. Thus, advancing from the contradicting results, we hypothesize that;

Ho3: There exists a positive and significant relationship between board tenure and firm performance

Moderating Effect of CEO Duality on the relationship between board attributes and firm performance

CEO duality has been defined as a state in which the Chief Executive Officer not only heads the company's operation but also chairs the board. Studies have referred this to as a double-edged sword. There are two conflicting theories on CEO duality. While agency theory advocates that the powers should be separated so that it can allow the board to control the CEO, stewardship theory views the CEO as a steward and a responsible executive who is ready to serve the interest of the owners of capital (Adams & Jiang, 2020; Kim, Al-Shammari, Kim, & Lee, 2009; Saleh et al., 2020)

The efficiency of the board depends on the powers that the CEO has over the board. While it is expected that the board should vet the powers of the CEO, this may not be the case, especially where he holds the two roles (Tang, 2017). In fact, in the case of duality, it means the CEO participates in the nomination of the directors. In such a case, they may choose a friendly board that he/she can efficiently work with. Secondly, the independence of the directors will tend to be compromised in fear of the contracts not being renewed. Thus, to establish the moderating effect of CEOs structural power on the relationship between boards attributes and firm performance, we hypothesized that;

Ho4a CEO Duality does not moderate the relationship between board independence and firm performance

Ho4b CEO Duality does not moderate the relationship between board size and firm performance

Ho4c CEO Duality does not moderate the relationship between board tenure and firm performance

Conceptual Framework

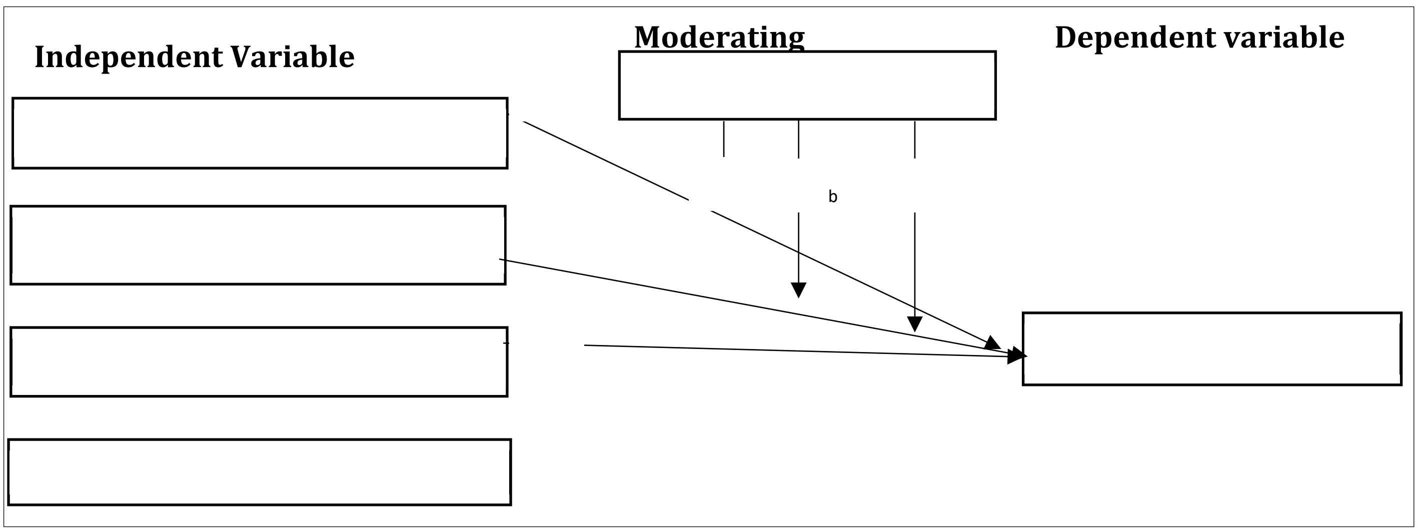

Figure 1 - Conceptual Framework of the Study

Research Methodology

The data were derived from published financial statements of listed firms in Kenya. The longitudinal research design was adopted in this research, targeting 51 firms actively trading at NSE between 2002 and 2017. Thus, the census approach was adopted.

Measurement of Variables

Dependent Variable

Firm performance refers to organizational effectiveness in utilizing the company's resources to consistently improve capabilities and abilities to meet the company goals. Previous research has measured performance using ROA and ROE (Buallay, Hamdan, & Zureigat, 2017; Lamb, 2017). Hence the current study adopted the measurements used by Subedi (2018) in measuring firm performance using a return on equity.

Independent variables

Board independence refers to where a director does not have a relationship with the company except as a director. The study followed Klettner, Clarke, and Boersma (2014) by measuring board independence as a proportion of seats held by neutral directors.

Board size referred to the aggregate directors in a given board. The study adopted Ntim (2016) by measuring board size as the composite of individuals serving a given board at a given time.

Board tenure refers to the period a director has served as a board member in an organization. The study followed Chan, Liu, and Sun (2013) approach by considering directors who have been in the organization for less than one year by converting duration into monthly equivalence.

Moderating Variable

Chief Executive Officer duality was defined as a combination of roles of board chair and CEO duties. This was measured as a dummy variable set to one if it existed; if not, then zero was denoted.

Control Variables

The variable that had shown influence on the dependent variable was controlled. That is firm size. This was measured as the natural log of total assets worth (Li, 2016).

Table 1: Measurement of variables

	Measurement
Endogenous Variable	
Firm performance	Measured using a return on equity (ROE)
Exogenous Variables	Number of independent directors serving a board
Independence of the board	
Tenure of the board	A period in which a board member as served the board.
Size of the board	The total number of directors serving a board.
Moderating Variable	
CEO Duality	The dummy variable set as to1 if there is CEO duality; otherwise, zero
Control Variables	
Firm size	Natural logarithm of total assets.

Regression Models

The models for this study were then specified as follows;

Model 1 presented the relationship between control variables and the dependent variable

$$Firper_{it} = \beta_0 + \beta_1 Firsize_{it} + \varepsilon_{it} \ldots\ldots \text{Model 1}$$

Model 2 presented the introduction of the direct effects

$$Firper_{it} = \beta_0 + \beta_1 Firsize_{it} + \beta_2 Boinde_{it} + \beta_3 Bosize_{it} + \beta_4 Boten_{it} + \varepsilon_{it} \ldots\ldots \text{Model 2}$$

Model 3 presented the introduction of the interaction effects

$$Firper_{it} = \beta_0 + \beta_1 Firsize_{it} + \beta_2 Boinde_{it} + \beta_3 Bosize_{it} + \beta_4 Boten_{it} + \beta_5 Ceodual_{it} + \beta_6 Boinde^{*} Ceodual$$

$$+ \beta_7 Bosize^{*} Ceodual + \beta_8 Boten^{*} Ceodual + \varepsilon_{it} \ldots\ldots \text{Model 3}$$

Where;

Firper (Firm performance) Firsize (Firm size) Boinde(Board independence), Bosize(Board size) Boten(Board tenure) CEOdual (CEO Duality)

Results

Descriptive statistics results showed that the average mean for the firm performance was 0.061 between and within the variation of 0.081 and 0.113, respectively. Board independence showed an overall mean of 0.821, meaning that at least 80% of the directors were independent. Board tenure showed that at least directors served for 10.923 years. The size of the boards showed an average mean of 9.37, while CEO duality and firm size showed an average mean of 0.015 and 16.27, respectively. However, none of the study variables showed a significant correlation with firm performance.

Before the regression model was fitted to test the hypothesis, it was necessary to carry out panel diagnostic tests and check for regression assumptions. First, all the variables were checked for panel stationarity, and the results had p values less than 0.05 indicating that all study variables exhibited panel stationarity. Hausman test carried out had p- values greater than 0.05, indicating that REM was the preferred model. Breusch Pagan, Langrange multiplier test also indicated that the data had panel effects.

Both model specification tests warranted the adoption of the random effects model as opposed to the fixed or pooled effect models. Since REM produce biased estimators in cases of unbalanced data, Swamy-Arora estimators were adopted. To adopt the results of the swamy-arora random effect estimates, further diagnostic tests were carried out on the model fitted. Table 2 presents the model diagnostic test results undertaken to check whether the model met or violated the classical linear model assumptions of random effect models.

Table 2: Diagnosis of model assumptions

Assumption/ Purpose	Test	Test statistic	P-value	Conclusion
Non-Serial correlation	Breusch-Godfrey/Wooldridge	F (1, 49) = 1.759	.1909	Not violated
Homoscedasticity	Wald	Chi2(52) = 3.05e+08	.0000	Assumption violated
Normality test (within)	JB test	chi2(2) = 3.52	.1719	Not violated
Normality test (between)	JB test	chi2(2) = 2.73	.2549	Not violated
Cross-sectional independence	Friedman test	Pesaran's Z = 1.140,	1.0000	Not violated

Since the model violated the homoscedasticity assumption, Integrated Generalized Least squares were used to take care of the heteroscedastic errors. Model 1 presented the relationship between the control variable and the dependent variable. Firm size showed a significant positive effect (β= 0.010, p<.05) with firm performance. Model 2 presented the relationship between control variables and dependent variables. Thus, the results were used to answer H_{o1}, H_{o2}, and H_{o3}. H_{o1} presupposed that there exists a positive and significant relationship between board independence and firm performance. The results showed board independence had a positive and significant relationship with firm performance (β= .065, p<.05). Thus, the hypothesis failed to be rejected.

H_{o2} proposed that there exists a positive and significant relationship between board size and firm performance. The results showed that board size had a positive and significant effect on firm performance (β= .011, p<.05). Hence the hypothesis failed to be rejected. H_{o3} presumed that there exists a positive and significant relationship between board tenure and firm performance. The results showed that board tenure had a positive and significant relationship with firm performance (β= .013, p<.05). Thus, the hypothesis failed to be rejected. Model 3 presented the introduction of the moderating variable together with interaction terms to test the

moderating effect of CEO duality on the relationship between board attributes and firm performance. Thus, the results were meant to answer H_{o4a}, H_{o4b}, and H_{o4c}. The coefficient estimates of the additional interaction terms showed no significance. Board independence interaction CEO duality showed (β = -.518; *p*>.05), Board size interaction CEO duality showed (β = -.093; *p*>.05) while Board tenure interaction CEO duality showed (β = .049; *p*>.05). Thus, it is deduced that CEO duality does not have a moderating effect on the relationship between board independence, board size, board tenure, and firm performance. The hierarchical results have been shown in the table below.

Table 3: Hierarchical Results

Variables	Model 1 Estimates	Model 2 Estimates	Model 3 Estimates
Intercept	-.319 (0.000)	-0.319 (0.000)	-0.318 (0.000)
Control Variable			
Firm Size	.010 (0.000)**	.010 (0.000)**	0.010 (0.000)**
Main Effects			
Board Independence		.065 (0.008)**	0.065 (0.005)**
Board Tenure		.013 (0.000)**	0.013(0.000)**
Board Size		.011 (0.000)**	0.011(0.000)**
Moderating variable			
CEO duality			0.693 (0.621)
Interaction effects			
Board independence interaction CEO duality			-0.518 (0.465)
Board tenure interaction CEO duality			0.049 (0.370)
Board size interaction CEO duality			-0.093 (0.548)
Summary statistics			
Loglikelihood	14.016	16.120	16.556
Chi-square	120.67 (0.000)	125.71 (0.000)	126.75 (0.000)
Likelihood ratio change (LR)		4.21 (0.0403)	0.87 (0.831)
AIC (Akaike's information criterion)	81.966	79.759	84.886
BIC (Bayesian information criterion)	334.875	334.620	353.400

Discussion

The study sought to establish how CEO structural power can influence the board's effectiveness in enhancing firm performance. The findings showed that increasing the independent members on the board would increase the board's effectiveness in enhancing firm value. This can be attributed to the fact that independent board members do not have any attachment to the company except the directorship role. Hence they would do their best to increase the firm's wealth. Secondly, they value their reputation because of the market; thus, they would do their best to increase their reputation. This result echoes the findings of Ciftci, Tatoglu, Wood, Demirbag, and Zaim (2019), who contended that when more independent directors are included in the board, an organization improves. Other studies that have been supported by the findings include (Fernandes, Farinha, Martins, & Mateus, 2017; Oteng-Abayie, Affram, & Mensah, 2018). The size of the board was also found to be influencing the performance of the organization, thus supporting the resource dependency theory. The reason attributed to this is because, as the board size is increased, it enhances the probability of increasing the inclusion of more expertise and more independent directors on the board. The results support the findings of Saleh et al. (2020) and Kalsie and Shrivastav (2016), who argued that when the membership of the board

members is increased, it increases firm performance. Board tenure was also found to be influencing firm performance positively. The main reason attributing to this is that as the board members serve a firm for a more extended period, they tend to understand its operations well. As such, they become more productive as compared to the shorter periods. These findings echo the study of Amaoko and Goh (2015) who found that increasing the board tenure proportionately increases the firms' profitability. The moderating effect of the Chief executive duality was however found to be insignificant and thus have no influence on boards' characteristics in increasing the firm value. Thus, the findings support the stewardship theory prepositions that managers are good stewards and thus focus in serving the interest of the owners of capital.

Conclusion

While it is widely accepted that good corporate governance is pertinent in the growth and performance of modern firms, the jury on CEO duality is still out. While some scholars are in favor of a firm's governance structure which upholds CEO duality because it allows for executive teams to run firms with clear leadership, thus facilitating effective communication between shareholders and investors, other researchers are vehemently against CEO duality governance structure by the claim that a CEO might become too powerful and unfavorably influence the monitoring function of the board. Thus, interfering with a board's oversight effectiveness and firm performance. It then suffices that there is neither right nor wrong board structure. However, investors and stakeholders are more persuaded to separate the roles to enhance independence and transparency.

Theoretical implications

The findings of this study add to the extant literature by providing other board constructs that can enhance firm value. Further, the moderating effect of structural power is established. Thus, it is evident that in the Kenyan setup, an increase in the membership of the independent board, increasing the board sizes, and the tenure of the directors increases firm value. However, the structural power of the CEO cannot change the efficiency of the board.

Practical implications

Kenyan listed firms should consider incorporating more independent directors, which increases the size of the board. Further, they should increase the period in which a director can serve a firm to increase efficiency and firm value.

Policy implications

The Capital Market Authorities in Kenya should consider revising the board requirements on the independence of the boards, tenure, and size as per the findings of this study. Moreover, delinking the powers of the Board Chair and CEO should not be mandatory, especially for the small growing firms.

Recommendations for further research

The research will act as a springboard for scholars in this field to build on and extend the outcomes of this study. Future studies should establish the relationship of other board constructs such as board diversity, multiple directorships, board educational diversity, or the board functional diversity and firm profitability. Also, the same study can be replicated to non-listed companies, NGOs, and family-owned businesses.

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